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Major Depressive Disorder and Labour Market Outcomes

Evidence from Finnish Administrative Panel Data

Master's Thesis
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Economics
Fall 2019

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Abstract of master's thesis

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Title of thesis Major Depressive Disorder and Labour Market Outcomes – Evidence from Finnish Administrative Panel Data

Degree Master of Science (Economics and Business Administration)

Degree programme Economics

Thesis advisor(s) Matti Liski

Year of approval 2019 **Number of pages** 50 **Language** English

Abstract

This master's thesis studies the effects of major depressive disorder on labour market outcomes, mainly earnings. Major depressive disorder has been shown to associate negatively with labour market outcomes. Most studies of this topic use survey data and are often constrained in the longitudinal sense. This thesis presents both short- and long-term results of the effects of depression on earnings from a series of 16-year event studies conducted on Finnish administrative data. Depression is found to decrease yearly earnings on average by around a month's median Finnish salary during the year of diagnosis with a decreasing long-term trend. The longer and more severe depression is the stronger the magnitude of the effect. Finally, large differences are found in the impact of depression on individuals on different earning levels with lower earners having a more consistent negative effect even before diagnosis and higher earners showing increased yearly earnings leading up to the diagnosis and a subsequent strong decline. Overall, long-term effects are negative for all the cases studied.

Keywords major depressive disorder, depression, labour market outcomes, earnings, event study

Acknowledgments:

This thesis was made possible by the assistance and support of many friends, family and colleagues. I would especially like to thank The Finnish Institute for Health and Welfare (THL) for making it possible to study this topic with this data. My sincere appreciation goes to all the staff of CHESS-unit, especially to my supervisor at THL, Research Manager Maria Vaalavuo, for her support, patience and flexibility, and equally to the Head of the Unit Mikko Peltola and unit assistant Jaana Aho. From Aalto-university I would like to thank my supervisor Prof. Matti Liski for his always positive and excited attitude towards research and my thesis.

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1. Introduction

Major depressive disorder, or depression, is a common and impairing illness with prevalence figures usually around 2-10% of the population. Symptoms and causes of depression can vary significantly. In Finland the prevalence of major depressive disorder has slightly increased since the turn of the millennia and in 2011 was estimated to be around 7.4% of the population (Paykel et al. 2005, WHO 2017, Markkula et al. 2017). In United States a 2010 estimate of prevalence was 6.8% of population (Greenberg et al. 2015). Depression is also more common in working age populations and it is a major cause of disability and disability retirement (Karpansalo et al. 2005, Sobocki et al. 2006).

The economic burden of depression is large and increasing. In United States incremental economic burden was estimated to have increased from 173.2 billion dollars to 210.5 billion dollars from 2005 to 2010 with approximately half of the costs coming from indirect productivity losses (Greenberg et al. 2015). In Europe, the annual cost of depression in 2004 was estimated to have been 118 billion euros or 1% of the European GDP with indirect costs accounting for over 65% of the total cost of a patient (Sobocki et al. 2006).

The connection between depression and labour market outcomes is a well-studied topic of research. There are plenty of findings that point to depression and in general mental health disorders affecting labour market outcomes. Several studies using various methods have found that mental health disorders and depression especially decrease the likelihood of employment. The effects between various studies fluctuate from 2 percentage points to at least 22 percentage points (Peng et al. 2013, Chatterji et al. 2007). The effect on work loss, work hours and earnings are also negative though less consistent. Ettner et al. (1997) estimated earnings drop due to psychiatric disorder to be around 3500 to 10 000 dollars for women. Lim et al. (2000) estimated that depressed fulltime workers have 1.4 mean work loss days per month more than non-depressed and 4.2 mean work cutback days. The magnitude and even direction of the effect of depression generally has been found to vary in many studies for example between genders. Such differences exist also between different earning groups with low earners suffering particularly of the negative effects depression has on labour market outcomes (Marcotte & Wilcox-Gök, 2003).

Most of the research in depression and labour market outcomes has been focused on short-term effects (Fletcher 2013), perhaps due to heavy reliance on large scale national surveys that are performed not on a yearly basis and may not follow the same individuals over the years.

This paper aims to answer the following questions:

- How does depression relate to labour market outcomes in Finland?
- Are the short-term negative effects found in many studies permanent or is there convergence back to the general population overtime, i.e. what is the time profile of impacts for individuals?
- Do the effects vary according to socioeconomic differences, i.e. do low and high earners have similar associations with depression?

The addition to previous literature comes essentially from the use of extensive registry level panel data of the full population of Finland. It is more precise, inclusive and trustworthy than surveys and allows for a much longer-term analysis. The labour market outcomes studied here are earnings, employment months and employer ownership status (public/private) in yearly observations. OLS-regression are run to determine the momentary effect of depression for the whole data set and long-term effects are researched in an event study setting with an event window of all together 16 years with 5 years prior to first diagnosis, year of diagnosis and then 10 years after the diagnosis. The effects are also studied separately for 4 different earning groups.

The results are consistent with previous literature and almost all the estimates are statistically significant. The yearly earnings decrease for those diagnosed with depression is approximately 3000€ with less severe diagnoses causing a slightly lower decrease and more severe diagnoses a larger decrease. Or in other terms, the effect is similar to losing around one month of current median salary of Finland. While magnitudes change with severity and duration the trend of the impact remains very similar between the various diagnoses. Large differences are found within different earning groups. Low earning groups behave similarly to the baseline regression with stronger magnitudes. Middle earning group shows a slightly more clear and exact temporal effect of the diagnosis, and high and top earning group show considerable increase in yearly earnings prior to diagnosis compared to control groups and a strong decline right after diagnosis. This suggests that lower earners are differently impacted by depression than those with higher earnings. This is likely due to differences in treatment seeking and availability as suggested by Marcotte and Wilcox-Gök (2003) but perhaps also due to increased co-morbidity or association with multiple problems at lower earning groups.

Career dynamics between the earning groups are likely different and might explain some of the differences in the impacts associated with depression.

2. Background

This section explains what depression is, what are its causes and effects thought to be and what is the theoretical link between depression and labour market outcomes. Previous empirical findings are discussed and how this study aims to add to the literature.

2.1 Defining depression

Depression is a common, complex and serious mood disorder. Depression is associated with a large array of factors ranging from stressful life events, to physical and psychiatric illnesses to genetics and to personality traits and disorders (Mazure C.M 1998, Goodwin G.M 2006, Levinson D.F 2006, Bagby et al. 2008). Finding a clear causal link to depression has proven much more difficult (Beck & Alford, 2014 p135-136). Despite depression being so arguably hard to measure and define accounts fitting surprisingly closely with modern definitions of depression and its symptoms survive since classical times and from various sources. Only the name has varied and for a long time what we call depression was known as melancholia (Beck & Alford 2014 p.7).

If causes of depression remain varied and debatable same is true of the symptoms. Associations between symptoms and depression are well recorded and studied but might vary significantly between individuals inflicted by depression. Beck and Alford (2009, p. 8) define depression broadly along these attributes:

1. A specific alteration in mood: sadness, loneliness, apathy.
2. A negative self-concept associated with self-reproaches and self-blame.
3. Regressive and self-punitive wishes: desires to escape, hide, or die.
4. Vegetative changes: anorexia, insomnia, loss of libido.
5. Change in activity level: retardation or agitation.

This simplified table shows symptoms criteria for depression diagnosis according to World Health Organizations International Classification of Diseases (ICD10) and provides a glimpse of what depression looks like:

Criteria for symptoms:	Symptom description:
A. Depression episode has lasted for minimum 2 weeks	
B. At least 2 of the following symptoms are	1. Depressed mood for most of the time
	2. Loss of interest and lack of pleasure from normally rewarding or enjoyable activities
	3. depleted energy or exceptional tiredness
C. One or several of the following symptoms are found so that B and C equal minimum 4	4. Loss of self confidence and self value
	5. Unfound or unreasonable self-accusations
	6. Repeated thoughts of death or suicide or self-destructive behaviour
	7. Subjective or observed difficulty in concentration, and possible indecisiveness and hesitation
	8. Psychomotoric change (decreased or increased)
	9. Sleep disorders
	10. Loss or increase of apetite that includes weight changes
Mild depression **4-5** symptoms, moderate depression **6-7** and major depressive disorder **8-10** with all of the B. symptoms. Psychosis includes further symptoms such as dilusions	

Figure 1. ICD10 based symptoms criteria for depression (modified from: Depressio: Käypä hoito -suositus 2016)

Treatment of depression varies across the different severities but generally for milder forms of depression psychotherapy is seen as sufficient on its own but even for moderate depression antidepressants are added to the pallet. Best results are reached with both antidepressants and psychotherapy (Depressio: Käypä hoito –suositus 2016). While treatment rates have increased still most patients either don't receive treatment or receive inadequate treatment (Hämäläinen et al. 2009, Kessler et al. 2005, Bijl et al. 2003). Increased severity is associated with increased treatment rates but even in the most severe comorbid cases 60% received treatment as estimated by Hämäläinen et al. (2008). In reality antidepressants are a more common treatment than psychotherapy and treatment rates fall below prevalence rates. Despite the inadequacies or failings of treatment even registering receiving treatment is recorded to relief of symptoms of depression and remission is found to be positive for work productivity and employment (Berndt et al. 1998, Mitra & Jones, 2017).

The depression studied in this thesis is essentially Major Depressive Disorders with the inclusion of Dysthymia and these together for the purposes of this study are referred to as depression. The actual diagnoses used in this thesis can be found in the section 4.1 Diagnosis data with the ICD 10 -codes.

2.2 Impacts of depression

The link between depression and labour market outcomes can be seen to include impairment of the individual's abilities related to such factors as memory, concentration, self-esteem among others, much related to the depression symptoms in general. It can also work through employer side with either discrimination or reluctance to accommodate for a depressed individual's needs. Additionally, the previous factors might lead to a decreased wage rate or on their own even lead to decreased labour force participation rates (Chatterji et al. 2011, Ettner et al. 1997).

One way how the depression related impairment of individual's abilities or will would affect labour market outcomes through productivity. This can happen either through presenteeism (lost work productivity while at work) or absenteeism (lost productivity due to absence from work). Absenteeism and presenteeism can hinder career building or even lead to unemployment (Peng et al. 2013). They are difficult to observe, especially presenteeism, as that information might only be available to the employee and/or employer. If productivity is lowered and if that is observable to the employer there would likely be adjustments to the salary or employment in general of the employee however such adjustments can take time as contracts are not exactly always short-term flexible. In temporary contracts the adjustment would be statistically perhaps more visible but for those in stable and permanent contracts salary and employment might take effect only in long-term, excluding incentive plans of course.

2.3 Previous empirical findings

Essentially two major problems exist in the econometric study of depression and labour market outcomes. The first problem is related to the measurement of depression. Studies of this subject are often based on self-reported survey data which can lack objectivity and might fail to catch the truthful levels of severity of depression or labour market outcomes. This can lead to measurement bias but also cause selection problems. On the other hand diagnosis data while being more trustworthy and precise as it is observed by a healthcare professional it also fails in certain aspects such as pinpointing the exact time of onset of the illness and as mentioned treatment rates usually fall far from estimated prevalence rates. Treatment seeking, resources and treatment availability are both likely causes for this. For example, the social stigma towards mental health illnesses is still a reality and can affect treatment seeking and (Roeloffs et al. 2003, Aromaa E., 2011).

Second problem with depression and labour market outcomes is the endogeneity between the two. As they are simultaneously observed it is difficult to ascertain the causality between them. This is also visible in research as there is a studied link from health to employment and from employment to health (Curie & Madrian 1999, Graetz 1993). Additionally, there can be a number of factors that affect both depression and labour market outcomes and which might be difficult to observe. Such unobserved heterogeneity could be caused by long-term effects of family backgrounds or co-occurring illnesses (Fletcher 2013). Third problem is that much of the previous studies have also relied on short-term links between depression and labour market outcomes (Fletcher 2013). This current research tries to answer some of these problems by using a very extensive and temporary long panel data that allows for both linking diseases and family backgrounds with individuals.

The earlier methods in determining the causal effect of depression on labour market outcomes relied heavily on instrumental variables. A common limitation has been the use of an instrument where the exclusion restriction is not exactly on solid grounds. It is indeed difficult to produce an instrument that affects labour market outcomes only through depression. As an example, commonly used instruments often fall within family and personal background factors such as parental depression, substance abuse, earlier mental health issues and other illnesses (Chatterji et al. 2007). While they have a clear association or even causality to depression, they do seem quite likely to also have some direct or at least indirect link, besides through depression, on labour market outcomes.

As an example of the results from the earlier studies Ettner et al. (1997) estimated major depression to lower employment rates by 8% in women and by 6% in men in United States. They found psychiatric disorders to cause an earnings drop from 3500 to 10000 dollars for women. For men the earnings effect was much lower and only statistically significant in ordinary form of their IV-results. Marcotte and Wilcox-Gök (2003) perform a similar study where they also measure quantile effects of earnings. Though rather inconclusive for most quantiles the lower quantiles showed a proportionally negative effect from depression. Using similar data but for Latin and Asian minorities in United States and similar IV's in a standard OLS and bivariate model setting Chatterji et al. (2007) estimate about 13% reduction from sample mean in the probability of employment for men and even stronger almost 40% for women.

More recent studies have relied on more statistical methods such as the selection into observables method proposed by Altonji et al. (2005) where selection into observables is used to gain information about selection into unobservables which was used by Chatterji et al. (2011). Their results were in similar range as those of for example Ettner et al. (1997) and though in contrast less conclusive for women. They suggest that females might have more complex selection issues compared to men. Using a fixed effects and correlated random effects models Peng et al. (2013) find significantly lower and often not statistically significant results. They find a negative effect on probability of employment of 2.6 percentage points and an increase in annual work loss days of 1.4 days which they extrapolate to cost in aggregate 700 million to 1.4 billion USD annually. Their data was from a two-year survey where each individual had 5 different observation points. Banerji et al. (2017) use a continuous rather than dichotomous measure for depression as an explanatory variable in an effort to account for the heterogeneity in depression diagnoses in an attempt to catch those who might not reach the threshold of diagnosis but nonetheless suffer from symptoms that cause impairment to work. They use standard and covariance IV's and a rank and replace model. They find that improvement in mental health increases employment by 18 and 11 percentage points for men and women. They estimate absenteeism cost to workplace to be 21.2 billion in 2002 dollars.

The limitations of the more recent studies are partly similar to those of earlier ones in terms of the data used. All of them use survey data and often an updated version of the same survey. In addition to the previously mentioned objectivity issues sometimes the quantity of data has been too low to for example estimate results for specific mental disorders. As for the more statistical methods used, for example in the correlated random effects model study by Peng et al. (2013) the factors that are supposed to catch the unobserved heterogeneity with regards depression are equally hard to prove as the earlier IV's. They used marital status, income of family members and physical and mental health status to model the random effects. As such their results are dependent of not having missed a factor that is time-varying and correlated with depression and not in their model. Considering that depression is time-varying it is quite possible that some of its causes or associations are so also.

As mentioned earlier the frictions in the labour market caused by for example contracts and labour market regulations is such in nature that some of the effects depression might have on labour market outcomes might not appear in short-term or might appear in different magnitudes than once there has been enough time for both employee and employer to adjust. Much of the previous literature has been either cross-sectional or limited in its longitudinal form. This current research tries to answer some of these highlighted limitations by using an extensive and quality panel data. The data is registry data of the full population of Finland observed and gathered by various authorities. As such the quantity and trustworthiness of the data is higher than in the previously mentioned survey studies. Additionally, as depression is diagnosed, and treatment is also observed this gives certain credibility to the explanatory variable as well. On the other hand, though those not treated are completely outside the reach of this data, something that survey might be able to catch. The long longitudinal form offers a rather unique opportunity to map the long-term effects or associations. The data also allows for a similar empirical strategy to be followed as with Chatterji et al. (2011) with the idea that selection based on observables would also hint of the selection to unobservables. The long-term effects are studied in similar event study manner as Kleven et al. (2019) studied the effect of having children on gender inequality.

3. Methodology

This section will explain the methodology used in this thesis. To answer the research questions of this study an empirical study is carried out using two slightly different methods. The first approach uses the whole available panel data to estimate the effect depression has on labour market outcomes, mainly earnings, in the year of the diagnosis, i.e. in the very short-term. This is done by a standard OLS regression. The second approach is in the style of an event study where a certain time window is derived with a certain event and the effect of the event is followed over time. The actual estimation is done with a standard OLS regression with an interaction between the event (depression diagnosis) and timeline. This is meant to model the long-term effects of depression on labour market outcomes.

The time before the event helps to evaluate whether the treatment and control groups used are plausibly similar by comparing the differences in the levels of the outcome variable and the trends that they show. A similar trend till the depression diagnosis would suggest that the effect is then fully related to depression or something else coincidentally happening that same year. Any deviation before diagnosis from the control groups trend might suggest that depression exists even before diagnosis or that something other than depression is also happening which is having an effect. This would suggest that the treatment and control group differ in terms other the just the depression. The after-diagnosis development helps to assess the permanency of the effects of depression and the consistency in the trend of the effect might give insight into the credibility of the depression as the cause. Other inexplicable shocks during the years after diagnosis to the treatment group would suggest that something else is also happening and that would eat the credibility of the estimated long-term effect.

The main outcome variable of this study is earnings which includes a variety of different earned incomes, basically an assortment of wages, salaries, benefits and reimbursements. The more special cases include various wages and benefits related to working at sea, but also incentive stock options and dividends based on labour input. The years from which each type of income is recorded varies but as the bulk of earned income is from basic salaries which are well recorded throughout the data set this shouldn't cause problems to the validity of the results. Earning figures are adjusted to inflation with base year being 1995, the first year in the data of this study. Additionally, employment months and employer ownership (private/public sector) are used as outcome variables. Other outcomes, such as company turnover and personnel size, were considered but they would have required different models and adjustments to the data, and these were outside the scope of this thesis. This is partially true with employment months and the employer company ownership status as well but are included nonetheless as their results are at least somewhat interpretable. Employment months are recorded since 1997 by determining each month individually with at least 16 days worked meaning a full month of employment and since 2005 according to days in employment throughout the whole year with the days being categorized to 12 months.

Ownership of employer in this study is narrowed down to whether company is privately or publicly owned. The interest in these additional outcome variables is that employees or employers might seek for a certain type of employment or employee. The issue is that companies can't exactly observe the individuals health condition but on the other hand individuals can't fully observe the atmosphere or workload inside the company either but they can have expectations of them and this might lead them to opt for certain type of choice. It is conceivable that individuals with long term depression might for example knowing their condition try and opt for a more stress-free working environment or for part time work.

Ideal models for the employment and ownership outcomes would be some form of generalized linear model and some logistic regression model. This is because standard OLS regression assumes linearity and employment is highly skewed to the 12 months end and ownership is a binary variable. As mentioned, due to the limited scope of a graduate thesis the analysis is constrained to a single model of regression and thus the conclusions of the additional outcomes are also limited.

Finally, an extensive list of controls is used in both the linear regression on the whole data and the event studies. The controls are gender, nationality, origin (background and birth included), language whether Finnish, Swedish or other, age, year of observation, municipality of residence, marital status, socio-economic group, highest educational level and the field of highest qualification/degree and the year it was attained, principal activity (employed, unemployed, student etc.), the number of children under 3, 7 and 18 and the number of special health care diagnoses other than depression by year (to estimate overall health). Most of these are not binary variables and conceivably the effect they have is not linear either and as such are treated as categorical variables with each category as their own dummy variable, such as municipality of residence with its hundreds of municipalities.

3.1 Linear regression

The linear regression is meant to show how depression affects labour market outcomes during the year in which depression is diagnosed. It is hard to argue that the estimates are purely causal as explained above the nature of depression and labour market outcomes is quite endogenous. Some of the effect is expected to be causal however and some evaluation can be done to estimate whether this is the case. The regression is run 7 times starting with only the outcome and explanatory variables (earnings and depression diagnosis) and with each regression adding more controls. Ideally, by adding more controls the main effect should stabilize and r2 should increase. This would suggest that omitted variable bias isn't playing a major role in the estimates and with some confidence the results could be understood as causal. Exactly what level of change and r-squared is acceptable is debatable and this wouldn't rule out reverse causality either.

Some of the weak points in the assumptions in this case include that the diagnosis data is available from only special healthcare which means that it is likely not a representative sample of depression cases in general in Finland but rather of more serious depression cases. Further, it is possible that in various extreme ends of outcomes the coefficients don't behave linearly compared to the whole sample. To counter this specific problem earnings are also categorized, and groups constructed from this are studied individually. This is further helpful in that the treatment group and control group would be as similar as possible.

Additionally, the reverse causality already mentioned is difficult to rule out completely, thus it is possible that some of the effect captured by the regression is in fact for example meager financial resources causing depression directly or indirectly. Also, it can't be completely ruled out that there isn't something in the error term that correlates with the depression or earnings. In fact, there is likely to be something there as depression is a complex issue with many causes and effects. However, that same complexity might lead to overall averaging out of the relationship between the error term and the depression as one factor left in the error term might affect individuals differently. The large quantity of observations and time in the data makes it easier to believe in the assumptions in general. With perhaps the exception that it is possible that due to the panel nature of the data there are shocks that the error term catches that correlate with the error terms of other observations such as the next year observation and this could lead to a regression estimates that aren't efficient in OLS terms.

3.2 Event study

The event of interest in this study is based on the first diagnosis of the various depression diagnoses. In the sort of baseline case the treatment includes all the diagnoses and as such estimates the average effect of having a depression diagnosed with ISD-10 (Figure 1) criteria. In events estimating the effect of the different severities and durations specific depression diagnoses are used. In the earnings group events, the baseline treatment is used but for a sample data constructed of the specific earning group. The chosen event window is 16 years with 5 years before the event, with year 0 being the diagnosis and then 10 years after the event. The event is constructed by the inclusion of the individuals who fit in the 16-year event window. Meaning that, for example, if an individual is diagnosed with first depression with the age 55, he is not going to be included in the event because the 10 years after event constraint cannot be satisfied as the data only includes individuals between the ages 20-60. Similarly, if a person is diagnosed with first depression at the age of say 22, the 5 years before event constraint is not satisfied.

As the event population is determined by having an event (depression diagnoses) and satisfying the constraints of being present in the data sufficient amount of years with regards the event this means that the event population includes individuals having event at different years. This allows the controlling of years and as such is meant to catch some of the time-varying effects, such as the nature of increasing earnings with time. It also allows catching a larger population for the treatment group than a cohort based on specific event year. Essentially the event window constraints mean that the first depression diagnoses in the event populations are between years 2000 and 2006. The basis for the control group consists of all the individuals who have never received a depression diagnosis.

The control group requires a similar 16-year window during which the analysis is constructed upon the same individuals throughout the years and as the treatment group varies with the time of their event it is necessary that the control group does so as well. The control group however doesn't have an event as in this case those who never have had depression belong to the control group. As such a fake "event" has to be constructed for the control group and it needs to be random so as it is as similar in behavior as the treatment event. The fake event is constructed by creating a dummy and giving each individual in the control group a single positive observation throughout their appearance in the data as quasi randomly as Stata, the statistical software used, allowed. With the fake event, similar event windows are constructed for the control. There would be those for whom the event appeared too late to fit 10 years after or too early to fit 5 years before, just as with the treatment group. This method will be referred later on as the randomized event.

As sensitivity check a type of cohort approach is also taken where the years 2000-2015 are studied with year 2005 being the first diagnosis of depression for the treatment group and similarly the fake event for the control group. This of course excludes every depressed individual who didn't have their first diagnosis during 2005 and thus the treatment group is smaller. On the other hand, the control group is bigger as now there are less individuals whose fake event happened closer to the begin or end of the data set. The randomization approach allowed for controlling years while the cohort approach causes a multicollinearity problem with years and the timeline of the event. The cohort approach produces similar results with regards the effect compared to control group but as years are not controlled the overall earnings are increasing throughout the event.

The event study just explained is mostly inspired by Kleven et al. (2003) who use similar method to estimate the effect of having children on the gender inequality of earnings. The event study in this thesis is less extensive and differs from that of Kleven et al. especially in the explained randomization.

3.3 Different diagnoses as treatment variation

The event study is also done with various treatment groups differing in their diagnosis. The different diagnoses for different severities and the separation of single and recurring diagnosis allows the study of both the effects of the severity of the depression throughout the years for the depressed individual but also the differences in effects between single episode and recurring depressions. The treatment groups of different severities are constructed so that they allowed the inclusion of only milder severities and durations. For example, single mild / moderate depression would only have those as it is the mildest diagnosis in this study whereas recurring severe diagnosis could include single mild / moderate, single severe, single severe with psychotic disorder and recurring mild / moderate. In each of the treatment groups the event is determined by the first diagnosis of the kind except for the recurring diagnoses where the first any diagnosis determined the event. This is necessary because in order to have a recurring diagnosis previous depression is ought to exist. Additionally, mild / moderate depression might change to severe with during later visits of the same episode of depression as the diagnosis becomes more precise. At the same time, it makes sense to exclude more severe depressions the milder ones because otherwise the trend observed after the diagnosis might be related to a relapse or continuing of the depression. Besides different diagnoses causing varying outcomes it is possible that individuals in different circumstances could have very different effects from depression.

3.4 Earning categories as sample difference

Constructing the data according to earning groups is done by dropping individuals who had never appeared in the specific earning category. For example, if individual throughout the event window never appeared to have earnings above middle earning group then they wouldn't be present in high earning or top earning samples. The movement between the categories of course is necessary in order to capture the correct outcomes thus naturally it is possible that, for example, before diagnosis individual is earning in high earning category but after the diagnosis drops to low earning category and vice versa and this is captured in the event study.

The groups are constructed from 12 earning categories. First category includes earnings from 0 to 9999.999 euros, the second from 10 000 to 19 999.999 and so on till the 11th category which goes from 100 000 to 149 999.999 and the 12th which goes from 150 000 to max. From these 4 groups are constructed with the intention of catching sufficiently representative groups. First group, called low, included only category 1, as it is a large category on its own, likely due to large amounts of students, part time workers and other miscellaneous earners. First group consists of approx. 25 million observations of which 525 000 are of depressed individuals. Second group, called middle, includes categories 2 to 4 with a large approximately 34 million observations of which 227 000 are observations of individuals with depression. Third group, called high, is built of categories 5 to 7 and consisted of 3.6million observations of which 8800 are observations of depressed individuals. The final group, called top, of categories 8 to 12, has 640 000 observations with 7300 observations of depressed individuals. These figures are of the whole data, the event studies of each case naturally are of smaller samples as explained above with how the events were constructed.

4. Data

This section explains what data is used in the study and some descriptive graphs are presented of the main variables such as gender, age, earnings and depression diagnoses. The data used in this study is based on registry data of the full Finnish population gathered by several different authorities. Earning figures are for example from the tax_authorities, diagnosis data from the Institute of Health and Welfare of Finland and employment data from employment ministry. As a whole the data used is stored and accessed through Statistics Finland. The set of data constructed for this study consists of the population of Finland aged 20-60 years old between the years 1995-2016. The variables that are expressed in euros, such as earnings, are inflation adjusted with the first year of the data, 1995, being the base year. The diagnosis data is of particular interest as it allows the identification of depression among individuals.

4.1 Diagnosis data

The method of identifying depression on an individual is based on the diagnosis by a medical professional. The diagnoses use the ICD-10 categorizations which includes a variety of different depression diagnoses mainly differing in the severity and duration. The diagnosis data used comes from special healthcare, or in other words secondary healthcare, and as such excludes primary healthcare, occupational healthcare and private healthcare. The diagnosis data includes years 1998-2016 and as such doesn't include the first three years of the whole data set. The idea behind this is to allow capturing of as many as possible depression cases in the event studies as the timeline window is from 5 years before to 10 years after. Thus, it allows the inclusion of depression cases from the year 2000. This logic would allow to start the data set as a whole from the year 1993 but due to some controls being recorded yearly only since 1995 and the idea to include a buffer, diagnoses of years 1998 and 1999, to be as sure as possible that the first depression diagnosis is actually the first lead to constructing the data set from 1995.

The ICD 10 lists a variety of diagnoses related to depression. To keep the number of explanatory variables to a reasonable level some diagnoses are grouped together. Not all diagnoses are given a unique group and as such are not studied separately, such as depressions with psychotic disorders. All the diagnoses are however present in the principal treatment variable that captures all major depressive disorders in secondary healthcare. The groups of diagnoses are as follows:

- Single mild / moderate captures all diagnoses in the ICD 10 list from F32 to F3211 meaning it consists of mild and moderate diagnoses including somatic and nonsomatic versions of both.
- Single severe captures only itself so from ICD 10 the F322
- Recurring mild / moderate follows the logic of single version of the same diagnoses and includes diagnoses from F33 to F3311
- Recurring severe captures only itself so from ICD 10 the F332
- Dysthymia captures only itself so from ICD 10 the F341

These 5 groups capture the vast majority of the individual depression diagnoses in the data. The following graph shows the sum of individuals through the years of the data who received these diagnoses (Figure 2). The upward trend in depression becoming at least more prevalently diagnosed is clear from the graph as is the increased duration of depression as the recurring diagnoses grow their share more rapidly. The prevalence rates are usually not found to be fluctuating by very much so it could be assumed that much of the upward trend in diagnoses is more due to treatment rates increasing.

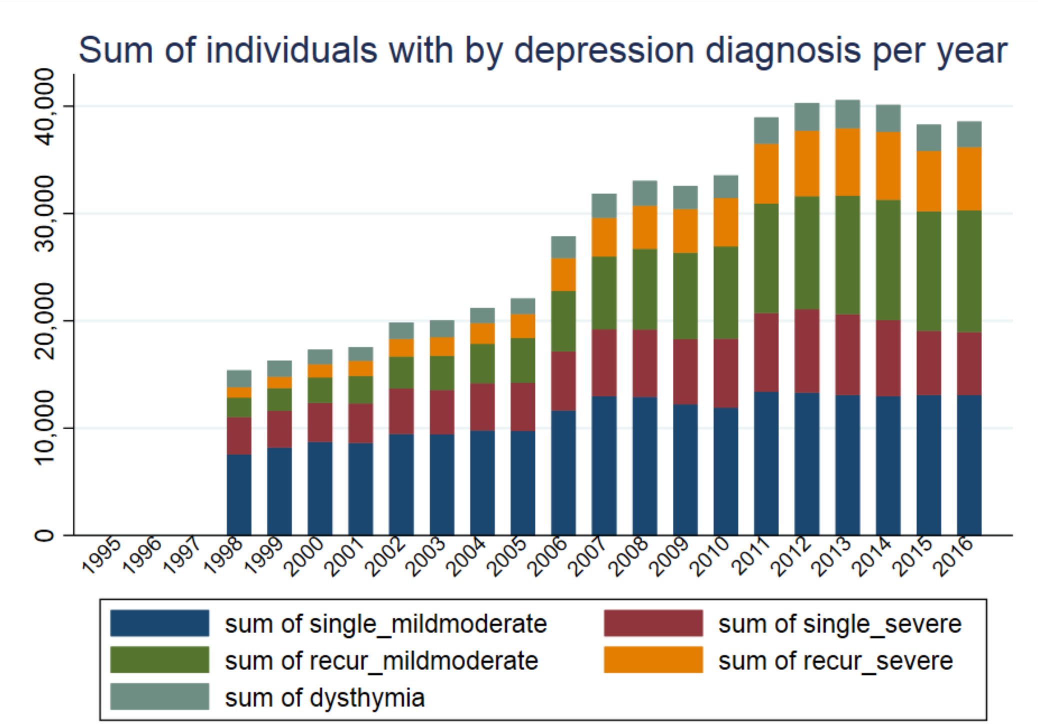

Figure 2. Sum of different depression diagnoses per individual per year

The amount of special healthcare diagnoses and hence visits individuals have per year on average is interesting because it tells something of the adequacy of the treatment. Of course, treatment received in other healthcare institutions is not visible so the overall adequacy of the treatment received cannot be ascertained with full confidence, but it is likely that a single visit in most cases is inadequate. The data showing a single visit per year per individual might be due to the depression being diagnosed late in the year and the next treatment following very soon next year or similarly the treatment end after several overall visits and only one visit is recorded for this reason for the last year. Graphing the density of the number of yearly visits per individual in percentages reveals that most individuals are treated in more than a single visit which accounts for approximately 30% of individuals and as mentioned this is likely overestimate (Figure 3). Still, single visit is bound to be inadequate in treating major depression and considerable quantity of those treated seem to be left at this level.

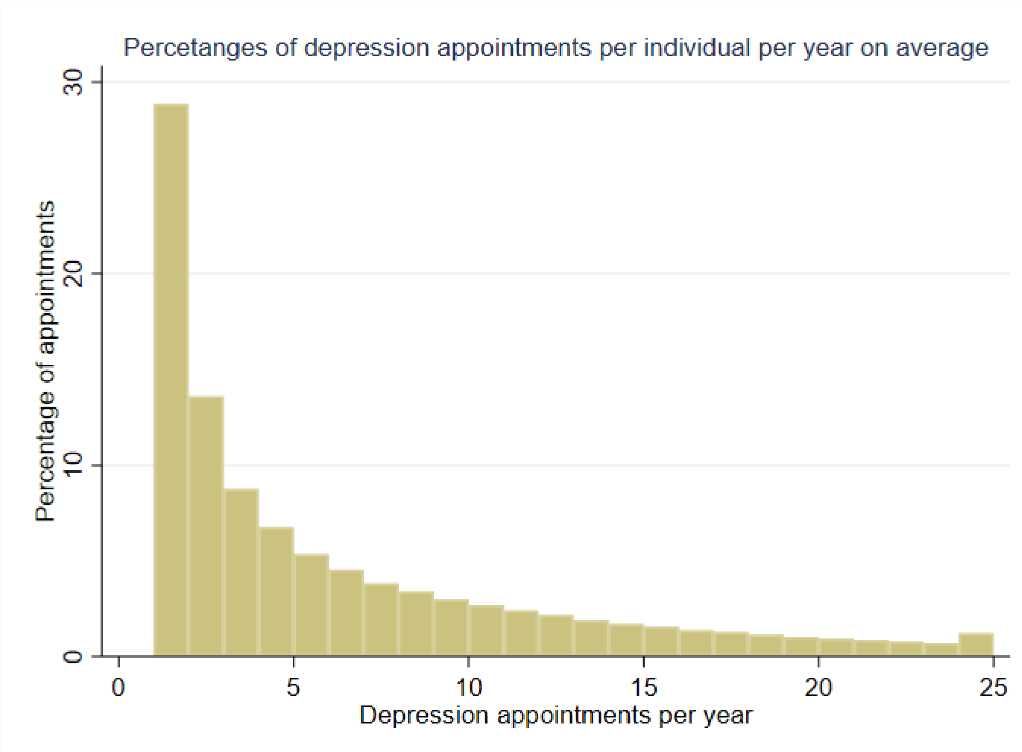

Figure 3. Average yearly depression appointments (visits with a depression diagnosis) in special healthcare per individuals in percentages calculated from 1998-2016 whole population

Depression diagnosis is received on average by individuals who are more likely to be female, earn less, have slightly lower education level, lower yearly employment duration and more visits to special healthcare, than those who are not diagnosed with depression. These ratios vary slightly according to the specific diagnosis with more severe diagnosis having lower mean incomes and longer duration diagnosis having slightly higher mean age and highest education levels. Gender ratio differs slightly as well with highest difference between single severe 61% women compared to recurring mild / moderate 70% women. Additionally, the more severe and the longer duration the diagnosis is the more debilitating it seems to be as for example demonstrated by the 0€ yearly earnings even at median for single severe, recurring severe and dysthymia diagnoses (Appendix 1).

Though mean age over the non-depressed and depressed is very similar and varies very little among different depression diagnoses the variation in age is quite different. Depression is more prevalent among the early 20's with lows in late 20's and 30's and increasing again during 40's with peaks in 50's (Figure 4). It's likely that the peaks in the prevalence at the beginning and at the late stage of career have different short- and long-term outcomes from one another and might require different type of policy interventions. This however is not the interest of this study. In the figure the density of non-depressed is also shown as a comparison of the general age distribution.

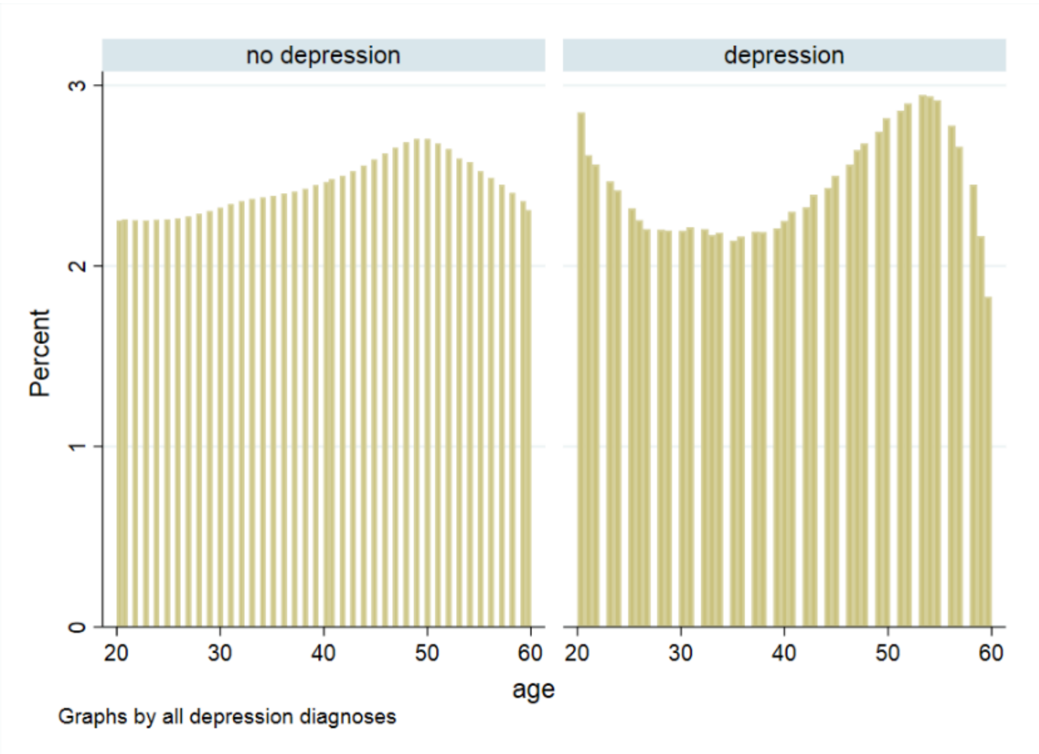

Figure 4. Density of observations by age in percentages. Depression more prevalent during early and late career.

Categorizing earnings in 12 different earning groups shows a skewness towards the lower earning groups but for the depressed group this is extremely strong with almost 70% falling within the lowest earning category (Figure 5). As mentioned earlier, this categorization is further divided into 4 earning groups in this study with lowest earnings consisting of the first category, middle earning group consisting of categories 2 and 3, high earning group consisting of 4 and 5 and top earning group consisting of the remaining group 6 and above.

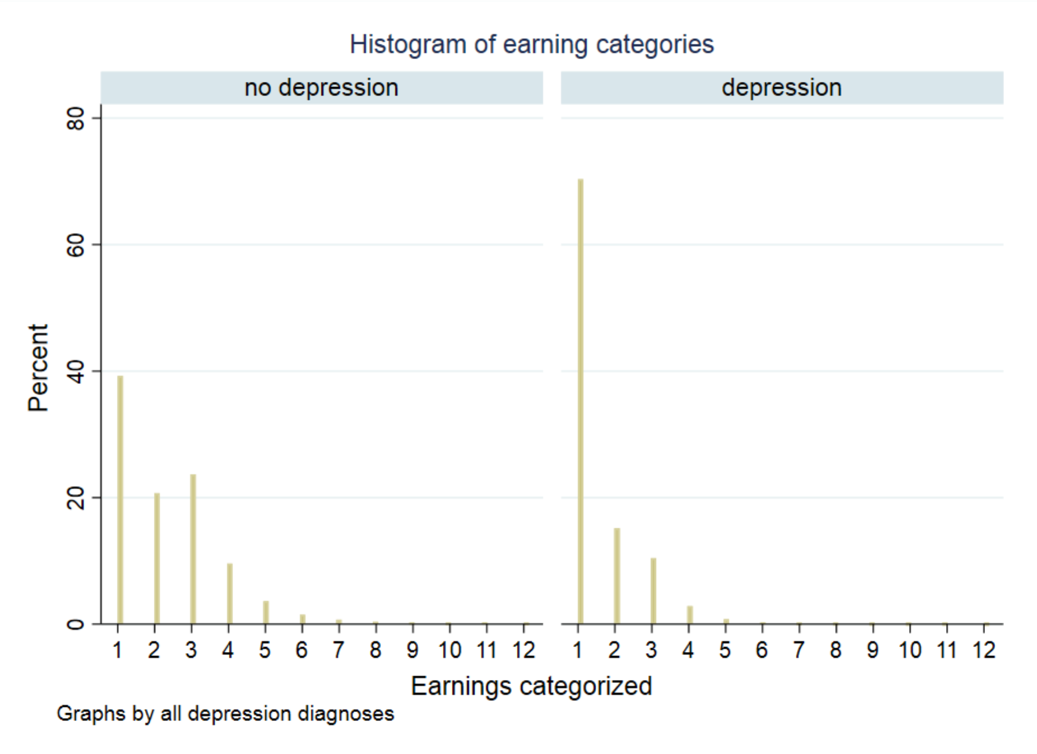

Figure 5. Density of observations by earning categories in percentages

All of the above descriptions are based on identifying a momentary specific diagnosis rather than comparing those who ever received a depression diagnosis and those who didn't. For the purpose of the event study such groups are formed in order to be able to follow the same individuals throughout the years. The above-mentioned earnings groups are created by individual having ever had belonged to a specific group, thus it is possible that an individual is present in more than one earnings group.

5. Threats to validity

This section discusses the limitations of the data and methodology and their significance. Some of the issues are repeated or referred to later when explaining the results of the study. There are several issues with the data that are not ideal. First, and much related to the second is that the data will not recognize depressions that haven't received a diagnosis. The omitted depressions are likely to a degree problematic in terms that they might have different outcome to the ones that we can observe. The ones who seek help or the ones who have the resources to seek and receive help are likely different from those who don't. The direction towards which this would bias the results is not obvious. There might be depressed individuals who don’t seek help but suffer nonetheless but without a clear impact on professional life. If this is commonplace the results obtained in this study would be more severe than in reality. It is also possible that the most extreme cases fall through the social welfare network or depression is not diagnosed amidst a myriad of other diseases and problems such as homelessness, alcoholism and other physical illnesses.

The second issue is that we are only using special healthcare data. This and the first point mean that the results reached in this study are not necessarily representative of the whole depressed population. Having only special healthcare diagnoses might have been a minor problem before as depression was often treated through special healthcare and perhaps even as inpatient treatment but for at least as long as the span of data in this study primary healthcare has been treating depressions, though some variation exists nationally between municipalities. Usually, if a depression is severe or long term enough primary healthcare will refer the case to special healthcare (Depressio: Käypä hoito –suositus 2016). Primary healthcare data was available for years 2011-2014 but considering the much longer span of the special healthcare data and the long event window in the event study this data is left out of the analysis. It can be noted that the number of yearly depression diagnoses is considerably higher in primary healthcare than in special healthcare.

The differences between those who receive special healthcare and primary healthcare are not clear. Usually, the depression treated by special healthcare is more severe and/or persistent, but this doesn’t necessarily tell much about the patients in general. As mentioned there might be differences between municipalities in that cases tend to be transferred to secondary healthcare more easily or rapidly.

Occupational and private healthcare are both not included in the data. This omission further means that the depressions observed in the data of this study might not be equal to depression in general or to those observed by other healthcare providers. Individuals with access to occupational healthcare or private healthcare have additional access points to healthcare and thus might have depression diagnosed and treated earlier and the effects of depression might therefore be less severe. Further, having access to occupational healthcare logically also means that an individual is earning an income and is likely to have at least better monetary resources than if they are unemployed and without occupational healthcare. Higher earnings and better occupational healthcare can mean better access and again perhaps better outcomes. Additionally, occupational healthcare might be a sign of other things such as better education, a more caring work environment and even better labour markets in general all of which can cause more positive outcomes compared to individuals who appear in secondary healthcare data. These differences might be caused not necessarily by being employed and having some access to healthcare but by being employed in a company that has very different occupational healthcare to the average. Companies can vary a lot in what all is included in occupational healthcare and there might be some correlations to what kind of salaries are paid.

The degree to which depressions from occupational healthcare are missing from secondary healthcare is not ultimately clear, however. Depression, even in a moderate form is usually treated with medicine and this means that special healthcare, i.e. psychiatrist, is required in order to prescribe the medicine, at least for a longer term (Depressio: Käypä hoito –suositus 2016). Usually occupational healthcare in Finland has some limits to the extent with which special healthcare services can be accessed through the occupational provider. Thus, it might be that at least some of the cases would also end up in primary or secondary healthcare and thus some might become visible in this data set as well.

In general, this data set likely includes cases that are to a degree more severe than the depression cases left outside the data. The descriptive statistics also hint that observed depression is suffered by individuals with on average worse resources (earnings for example), more health issues, less education and less stable employment compared to the general population (Appendix 1.) which probably also means that they differ in characteristics that are not observable in this study. The positive aspect is that dividing individuals into different earning brackets is possible and the effect of access or differences between socioeconomic groups can thus perhaps mitigated to an extent even with this data.

On the methodological side the most glaring limitation is perhaps that depression is observed through diagnosis and that depression can exist without diagnosis. This means that the exact time of the onset of depression is likely not accurately observed as help is rarely sought or found immediately (Hämäläinen et al. 2004). This essentially is the same as the first limitation highlighted with the data but considering that the effect captured in the regressions is in fact the effect of the diagnosis of depression it is noteworthy enough to mention twice. In fact, arguably the results could be interpreted as what effect does treating depression have on the labour market outcomes. The fact that treatment is being received however does not result to depression not existing or having an effect on labour market outcomes. Depression being diagnosed by a professional, compared to self-reporting, does improve the quality of the observation and gives some indication of time for the onset. As such, the limitation is also a strength.

6. Results

This section explains the results of this study. First, the results of the OLS-regression on the whole data showing the association that receiving a depression diagnosis has on earnings, employment months and employer ownership for the year of the diagnosis, i.e. the short-term relationship. Second, the event study results that show a light on the long-term development of the labour market outcomes before and after the first diagnosis of depression which is based on the 16-year event window.

6.1 Linear Regression

The relationship between depression diagnosis and earnings is quite strongly negative. The regression with just the outcome and treatment variables, tells that a depression diagnosis on average shows as -9730€ in yearly earnings compared to those who haven't received such a diagnosis. The actual effect of the diagnosis is not as large. As controls are added the impact decreases significantly, especially with education and principal occupation controls. After successively adding controls the main effect stabilizes to around -3000€ however with an r-squared of 0.290 considerable amount of the variation in earnings remains outside the coefficients of the regression (Table 1). This is somewhat to be expected as earnings is arguable complicated to predict but also not necessarily linear in nature especially at the higher end. The similar regression run on different earning groups produced slightly higher r-squared for the low and middle groups, 0.394 and 0.429 respectively, and slightly lower for the high and top groups, 0.241 and 0.154 respectively (Appendix 2). This is intuitive as well as it is likely that the very high earnings have explanations that are either difficult to catch or simply omitted from this study such as luck, networks and family backgrounds. The fact that age, year and municipality controls increase the negative effect of the diagnosis might be due to the age distribution of depression and the increasing treatment rates overtime. The effect of municipalities is not clear, the fact that the data is of special healthcare might play a role and it is possible that depression is more common in areas with poor labour market outlooks. All in all, the effect captured in this model is around a month's median Finnish salary.

Table 1: Linear regression of depression on earnings

	Dependent variable: Earnings						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Depression diagnosis	-9730.1***	-9066.2***	-10670.5***	-3292.9***	-3307.3***	-3048.4***	-2957.0***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gender		-4673.9***	-4871.7***	-4954.1***	-5065.4***	-5040.9***	-5744.6***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Nationality	No	Yes	Yes	Yes	Yes	Yes	Yes
Birth Origin	No	Yes	Yes	Yes	Yes	Yes	Yes
Native Language	No	Yes	Yes	Yes	Yes	Yes	Yes
Age	No	No	Yes	Yes	Yes	Yes	Yes
Year	No	No	Yes	Yes	Yes	Yes	Yes
Municipality	No	No	Yes	Yes	Yes	Yes	Yes
Highest education level	No	No	No	Yes	Yes	Yes	Yes
Field of highest education	No	No	No	Yes	Yes	Yes	Yes
Principal occuption	No	No	No	Yes	Yes	Yes	Yes
Marital status	No	No	No	No	Yes	Yes	Yes
#Children under 3	No	No	No	No	Yes	Yes	Yes
#Children under 7	No	No	No	No	Yes	Yes	Yes
#Children under 18	No	No	No	No	Yes	Yes	Yes
#visits to SHC	No	No	No	No	No	Yes	Yes
SocioEconomic Position	No	No	No	No	No	No	Yes
Year of graduation	No	No	No	No	No	No	Yes
R-sq	0.002	0.015	0.085	0.239	0.241	0.241	0.290
N	63527984	63527984	63527984	63527984	63527984	63527984	33068076

Notes 1. Results from a linear regression of earnings. Special healthcare diagnosis of depression as an independent variable with a variety of controls. Gender is binary (1 female), #visits to SHC counts the number of visits to special healthcare per year that is under different diagnosis than depression. The rest of the controls are categorical variables treated as individual dummies. Principal occupation refers to labour force status, whether employed or unemployed, student, pensioner, conscript, etc. Socioeconomic position is formed according to main type of activity, occupational status and industry. Same controls are used in all the regression in this study. The effect is of yearly earnings in euros. The regression is based on 1995-2016 data with earnings adjusted for inflation with base level at 1995. N is the number of observations in the regression.

The connection between depression and employment is also negative. As with earnings, what the connection between solely employment months and depression shows is much stronger than when controls are added going from -1,3 months to -0.48 months. Contrary to earnings r-squared is much higher at 0,46 with all the controls. Again, education and principal occupation shift the r-squared the most and as with earnings age, year and municipality increase the negative effect. The effect of principal occupation, or main activity, is quite logical as it shows whether an individual is gainfully employed, unemployed, student, pensioner, conscript or otherwise outside the labour force and as such it is expected to have a clear effect on labour market outcomes (Table 2). While this model is not ideal for explaining the employment months it likely captures the correct direction the very least. It is very likely that diagnosis would have a negative impact on employment months as depression is highly associated with disability leave and disability retirement (Karpansalo et al. 2005).

Table 2: Linear regression of depression on employment months

	Dependent variable: Employment months						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Depression diagnosis	-1.331***	-1.288***	-1.544***	-0.497***	-0.487***	-0.455***	-0.484***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gender		-0.280***	-0.292***	-0.161***	-0.163***	-0.160***	-0.125***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Nationality	No	Yes	Yes	Yes	Yes	Yes	Yes
Birth Origin	No	Yes	Yes	Yes	Yes	Yes	Yes
Native Language	No	Yes	Yes	Yes	Yes	Yes	Yes
Age	No	No	Yes	Yes	Yes	Yes	Yes
Year	No	No	Yes	Yes	Yes	Yes	Yes
County	No	No	Yes	Yes	Yes	Yes	Yes
Highest education level	No	No	No	Yes	Yes	Yes	Yes
Field of education	No	No	No	Yes	Yes	Yes	Yes
Principal occuption	No	No	No	Yes	Yes	Yes	Yes
Marital status	No	No	No	No	Yes	Yes	Yes
#Children under 3	No	No	No	No	Yes	Yes	Yes
#Children under 7	No	No	No	No	Yes	Yes	Yes
#Children under 18	No	No	No	No	Yes	Yes	Yes
#visits to SHC	No	No	No	No	No	Yes	Yes
SocioEconomic Position	No	No	No	No	No	No	Yes
Year of graduation	No	No	No	No	No	No	Yes
R-sq	0.001	0.006	0.162	0.508	0.509	0.509	0.460
N	49319110	49319110	49319110	49319110	49319110	49319110	27847209

Notes 2. Results from a linear regression of employment months. Special healthcare diagnosis of depression as an independent variable with a variety of controls. Controls explained under table 1. And in section 4. Data. The effect is of months of employment in a year, i.e with all controls depression shows as an approximately half a month decrease in yearly employment.

The final labour market outcome studied is type of ownership of company, simplified in this study to private/public dichotomy. As with employment months the reason is to both try and see what the path for the lowered earnings might be and to understand what effects depression has on labour market decisions in general. For example, one possibility is that depression affects the long-term labour market decisions leading to jobs that are less demanding and thus perhaps also monetarily less rewarding. With all controls depression is associated by 1.7% higher probability to work in the public sector with an r-squared of 0.333 (Appendix 3.). The problem with employment months and private/public sector outcome is that they're highly skewed as in the case of employment months or binary as in the case of private/public variable. The employment problem could be solved by converting the observations into log format, but the issue is how to deal with the 0's. It ought to be possible with a generalized linear model in Stata. As for the private/public sector employer a logistic model would be better suited for estimating a binary outcome. These models were left out of this thesis however due to the scope of the thesis. As such the results of employment months and public sector ought to be taken with a grain of salt.

The overall momentary results on the whole 22-year data show that depression is associated with considerable negative impacts on labour market outcomes both in earnings and in employment. Some of the effect might still be due to labour market outcomes causing depression or due omitted variable bias. For example, over demanding or over stressful work environment might lead to depression but at the same time dead end career prospects at current employment or diminished income might do to same. One thing that might cause doubt over the large rather immediate negative effect on earnings and employment that depression seems to have is that earnings and employment are necessarily flexible in short-term. It could be that for some reason depression is more prevalent amongst those employed with temporary contracts or in the gig-economy as renewing contracts has more momentary flexibility. At the same time though, depression is a serious illness and not necessarily treated immediately as symptoms arise and as such by the time diagnosis is received the effects of it might be showing up even in less flexible labour market outcomes.

It is probable though that some of the effect on labour market outcomes will not be manifested in the year of the diagnosis and such a long-term effect are perhaps even of more interest. It could be that some effects show only later when contracts have time to adjust and thus there might be negative effects later on as well. On the other hand, if treated one would expect some convergence to previous state or towards those without depression. For the purpose of studying the long-term effects an event study is constructed, the results of which will be explained in the next section. The effects are also studied for different earning groups and for different severities of diagnoses and durations.

6.2 Event study

The idea of the event studies is to look at how the outcome variables act before and after the event, the diagnosis of depression. It might seem odd to try and explain an outcome with something that did not happen till later, as if the future was known already. Why would a depression that does not exist yet and individual has no idea about have any effect on earnings right now? Main reason for analyzing the behavior prior to diagnosis is to see whether the treatment group, the diagnosed, and the control group, the never diagnosed, differ already before the event/treatment. In addition, and especially true with depression is that likely the depression in many cases existed to a degree before the actual diagnosis was received and thus might have had effects before its observation. A negative trend sometime before the actual diagnosis might be a sign of depression and effects caused by it already at that time and as such might also indicate either reluctance to seek treatment or the difficulty of receiving it. By dividing the observations to earning categories it might be possible to see differences in, for example, access to healthcare. Comparing the severities of the depression and especially duration ought to give indication on how successful the treatment is in terms of labour market outcomes. Caveat here is that primary healthcare data is excluded, and it is impossible to say whether later episodes exists but are treated elsewhere.

First, the baseline results are explained. As with the OLS on the year of the diagnosis effects the main result here is also of the treatment that includes all depression diagnoses. Second, the differences between the severities and durations of diagnoses are explored. Third, the treatment and control groups are categorized by earnings to see whether the results differ between earnings groups and fourth a look into the cohort method results to see if perhaps the chosen randomization method causes bias.

The main result of the event study is that the treatment group shows a decline in income starting from the beginning of the event window with a stronger decline during a three-year period around the actual event, the diagnosis of the depression. The results from the interaction regression are not statistically significant for the treatment group until 2 years prior to the diagnosis and for the control group one a year prior to the fake event. This is not particularly surprising as especially in the case of the control group there isn’t anything in the fake event that even should explain earnings. After the year 0 it makes some sense as predicting future earnings with past earnings is a somewhat convincing. As for the treatment group it is possible that some of the statistical significance prior to year 0 is due to on average catching some of the effects of the depression that occur prior to seeking or receiving diagnosis (Table 3).

Table 3: Linear regression of the interaction of depression diagnosis and 16 year event window on earnings

		Dependent variable: Earnings			
		No depression		Depression	
		b	ci95	b	ci95
	depression diagnosis ever	0	[0.00 0.00]	-770***	[-989 -550]
Depression * timeline interaction	year: -5	0	[0 , 0]	0	[0 , 0]
	year: -4	7	[-78 , 91]	-209	[-518 , 100]
	year: -3	71	[-17 , 159]	-495**	[-804 , -187]
	year: -2	112*	[21 , 203]	-714***	[-1022 , -406]
	year: -1	51	[-43 , 146]	-1009***	[-1316 , -701]
	year: 0	95	[-3 , 194]	-1651***	[-1959 , -1344]
	year: 1	122*	[19 , 224]	-2234***	[-2541 , -1927]
	year: 2	190***	[84 , 296]	-2451***	[-2758 , -2144]
	year: 3	221***	[111 , 331]	-2715***	[-3021 , -2408]
	year: 4	228***	[115 , 341]	-2989***	[-3295 , -2683]
	year: 5	240***	[123 , 357]	-3134***	[-3440 , -2827]
	year: 6	241***	[121 , 361]	-3269***	[-3575 , -2963]
	year: 7	203**	[80 , 326]	-3371***	[-3677 , -3065]
	year: 8	202**	[75 , 328]	-3414***	[-3720 , -3108]
	year: 9	203**	[73 , 333]	-3503***	[-3808 , -3197]
	year: 10	201**	[66 , 336]	-3622***	[-3928 , -3317]
	Controls	yes			
	R-squared	0.279			
	Observations	7331801			

*Notes 3. Linear regression on earnings with an interaction between depression diagnosis (ever having had one) and 16-year timeline as an explanatory variable where year 0 is the year of first diagnosis of depression. For the control group, i.e the individuals who have never received a depression diagnosis, the year 0 is a fake and randomly assigned "event". Depression diagnosis ever shows the effect of belonging to the treatment group and the depression * timeline interaction shows the yearly effects. All the same controls are included as in the standard linear regression of before.*

The table shows the estimates for belonging to the treatment group, i.e. depression diagnosis ever, and the interaction of time and having had depression. The column b shows these various estimates with column ci95 showing the 95% confidence interval and stars showing the level of statistical significance (* 0.1, ** 0.05, *** 0.01). The control (no depression) and treatment (depression) groups are separated to their own columns. R-squared and number of observations in the regression are shown at the bottom of the table. The results show that the two groups initially are already different in yearly earnings with treatment group at -770 euros compared to control group. The interaction of the 16-year timeline and not ever having had depression, meaning the control group shows a stable level of earnings throughout the timeline. Here the year 0 catches a completely fake and random "event" that should have no effect on their earnings, which it doesn't. The interaction of timeline and having a depression is more interesting and is detailed under its own column.

The regression shows, for the treatment group, a drop of over 500 euros in yearly earnings from two years to one year prior to the diagnosis and over 600 euro drop from one year prior towards the year of the diagnosis and a further over 500 euro drop for the year after diagnosis. At this point then, one year after the diagnosis the difference between the treatment and control group in earnings is about 3000 euros, of which about half happened already prior to one year before diagnosis. After this point each year shows a steady but slower decline in earnings. At the end of the 16-year event window the treatment group stands over 4000 euros lower in yearly earnings compared to control group. The trend is consistent and downward. The event population is 7,331,801 and the r-squared 0,279.

A predictive margins plot is constructed from the regression results. The horizontal axis shows the timeline of the event window and vertical axis depicts the yearly earnings in euros. The timeline is shown in form of 5 years before the event, the minus years, the year of the event being year 0 and marked with a vertical red line and then 10 years after the event. The colored areas show the 95% confidence interval of the earnings. The main purpose of the plot is to offer a visual representation of the interaction time and depression has on earnings. The downward trend is very consistent and easily observed from the plot as is the stagnation of the control group. What that shows is that the model captures quite well the time variant effects on earnings as the control group shows very little change overtime (Figure 6). Further event study results will be shown in the visual format.

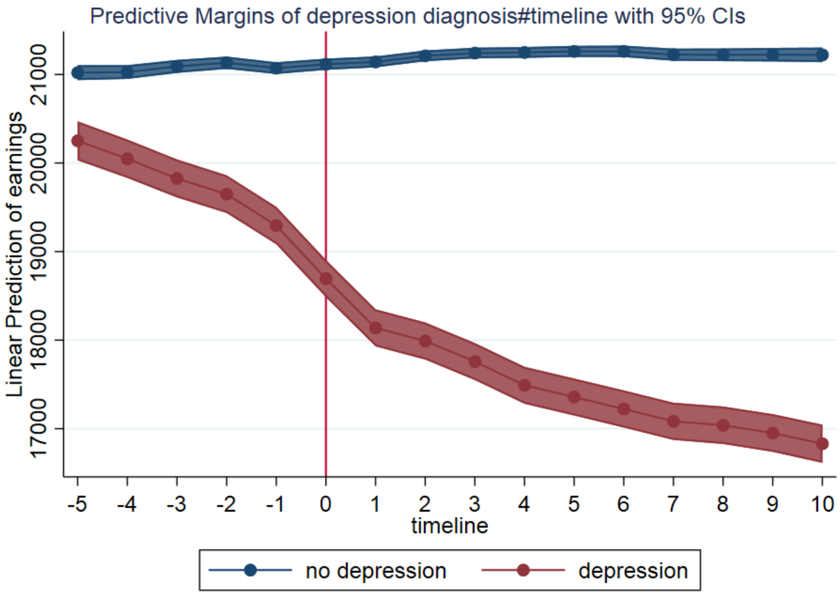

Figure 6. Predictive margins plot with earnings as outcome and explanatory variable as the interaction of a binary variable signaling any depression diagnoses and the event window timeline of 16 years with year 0 being the year of event, i.e the diagnosis.

Same regression and predictive margins plot but with employment months as an outcome variable show the treatment group trailing the control group by about half a month of yearly employment with clear decline during the years around the diagnosis (Figure 7). Opposite to earnings employment seems to climb after the diagnosis and in the end converge towards control group compared to the state at which the event began.

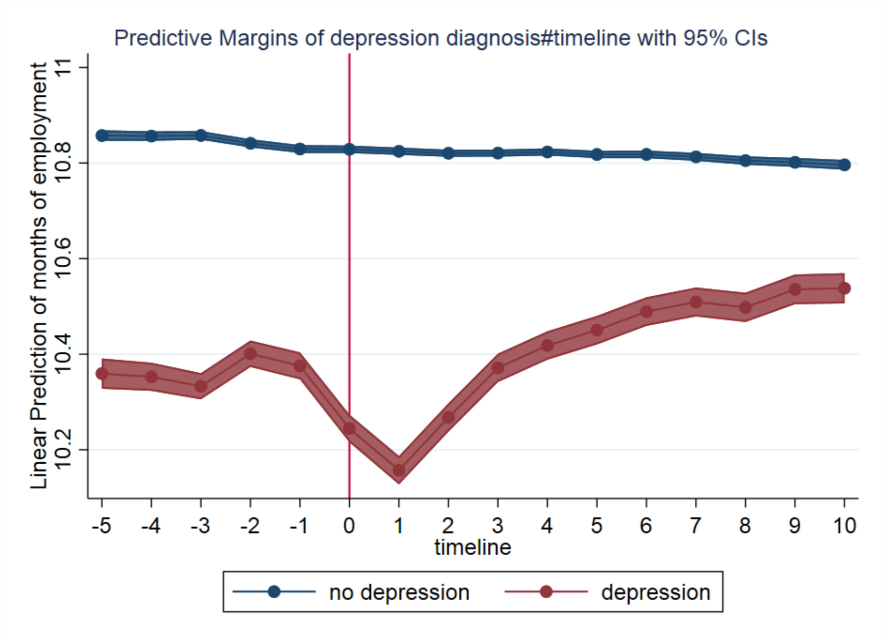

Figure 7. Predictive margins plot with months of employment as outcome variable and explanatory variable as the interaction of a binary variable signaling any depression diagnoses and the event window timeline of 16 years with year 0 being the year of the event, i.e. the diagnosis.

There seems to be a discrepancy between the earnings and employment months results. It could be that this is due to lowered productivity because of the depression and the negative effects it has on earnings, but it is also possible that the employment month regression is missing something included in the earnings regression. The number of missing observations in the employment variable in the whole data set is over 14 million, out of the approx. 63.5 million. Earnings are missing only from approximately 500 000 observations in the whole data set in comparison. Part of the missing is explained by that the employment observations only start from 1997 but that only explains about over 4 million of the missing. Whether the rest is due to having a purely random sample of the employment figures or due missing a particular group is unclear. Comparing missing observations amongst different principal occupation groups doesn't reveal anything consistent for example. This omission of observations is present in all of the employment regression and thus in the predictive margins plots as well.

One curious finding is that while the earning outcome results during the event year mimicked closely the short-term results for the employment months its quite different. The two groups start already at the different level with the diagnosis effect in the short-term regression and during the event fall below it. Though the changes are minimal around a fifth of a month. Overall though, if these results are taken at face value, employment time cannot explain the drop in earnings.

As for principal owner of the employer organization the treatment group is approximately 2% more likely to be employed by a public organization at the beginning of the event. There is a decreasing trend till one year prior to diagnosis which is followed by two years of increasing share of public ownership up to the starting point. After the trend is decreasing again till a slight upsurge during final years of the event. The confidence interval is such though that you could draw a horizontal line through the whole event window for the treatment group and at the same time besides perhaps the period around the event year there is little consistency in the trend (Figure 8). Perhaps the only clear thing to draw from this is that the depressed have a slightly higher tendency to work at the public side.

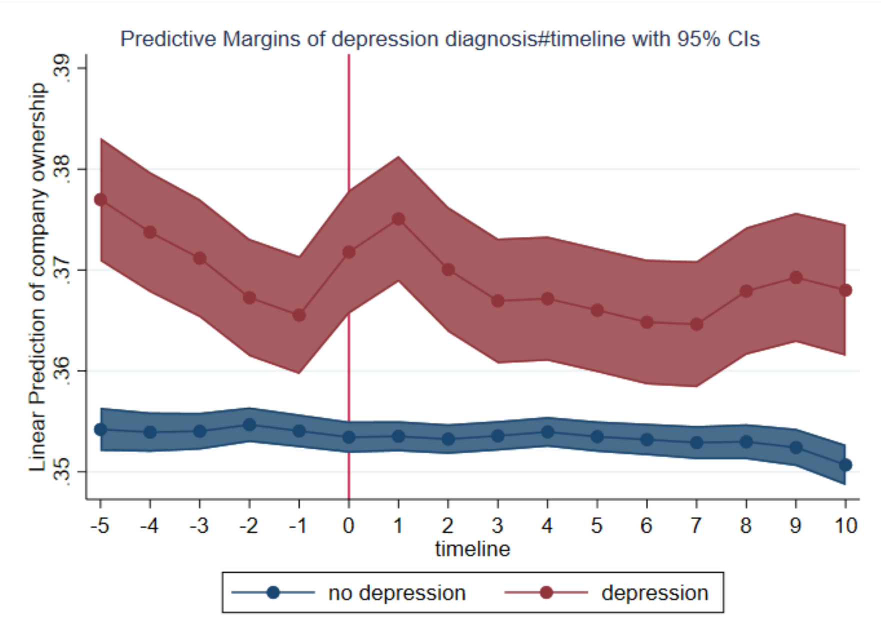

Figure 8. Predictive margins plot with ownership of employer (binary 0 private – 1 public) as outcome variable and explanatory variable as the interaction of a binary variable signaling any depression diagnoses and the event window timeline of 16 years with year 0 being the year of the event, i.e. diagnosis

6.3 Depression severity and duration

Severities and durations ought to show as different outcomes. More severe depression means more severe symptoms and thus likely it is more debilitating. The continuation of the depression ought to show as more negative long-term effects as well. Some of the continuing negative trend demonstrated in the earnings in the treatment group including all of those diagnosed with any depression might be explained by the very negative trend that continued depression could cause. On the other hand, a single mild to moderate depression with no signs later on might show convergence better than the average all depression included case.

As expected in the case of least severe diagnosis the results are not as negative as in the general case of all diagnoses or with more severe diagnoses. However, the overall negative trend is very similar and doesn't show any sign of leveling off or converging back towards control group. The statistical significance of the interaction fluctuates a little more before the diagnosis, though the effect of pertaining to the treatment group keeps the overall effect below control. The confidence interval narrows one year before the diagnosis. Overall, the 95% confidence interval is larger than in the general case. The treatment group and control group differ about 250 euros less in the beginning than in the general case. The year of the diagnosis the effect of the interaction is about 300 euros less and the effect at the end of the event window is almost a thousand euros less compared to the general case. So, while the magnitude is different the direction and trend are very similar (Figure 9).

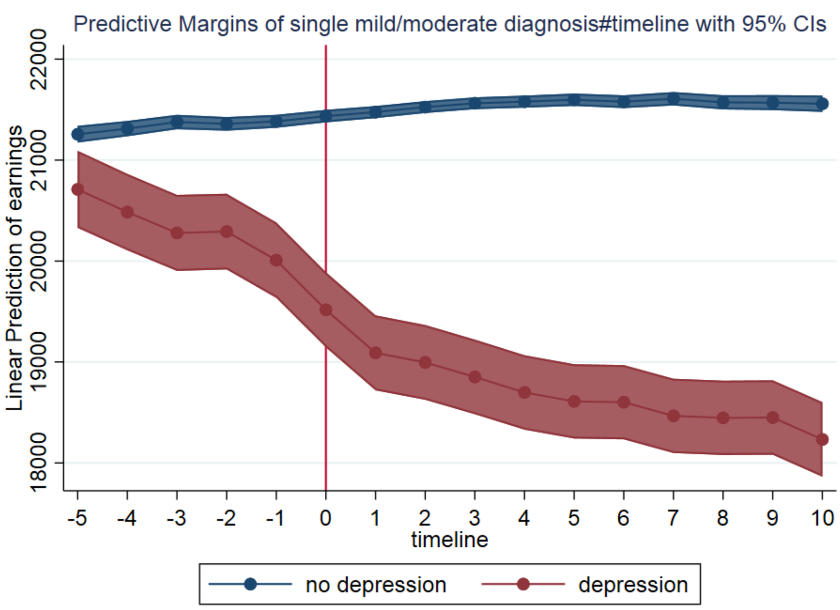

Figure 9. Predictive margins plot with earnings as outcome and explanatory variable as the interaction of a binary variable signaling single mild / moderate depression diagnosis and the event window timeline of 16 years with year 0 being the year of event, i.e. the diagnosis

Employment outcome follows a similar trend to that of the general all depressions case and again with less severe effects. The difference in the beginning is about a third of a month and though the effect during the years around the diagnosis is even a little bit stronger the convergence towards to control group is also stronger than in the general case. It is curious that earnings fall so strongly while employment months even manages to increase from levels during beginning of the event window as with the general case (Figure 10).

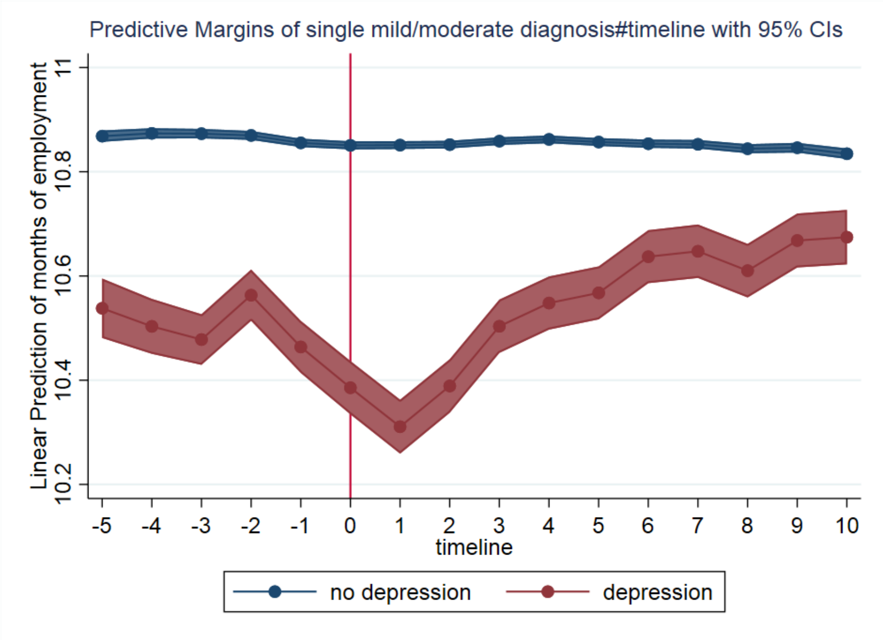

Figure 10. Predictive margins plot with months of employment as outcome and explanatory variable as the interaction of a binary variable signaling single mild / moderate depression diagnosis and the event window timeline of 16 years with year 0 being the year of

All the different diagnosis groups behave very similarly in terms of trend and levels of effects on earnings (Appendix 4). Minor difference is to be found as in the case of dysthymia diagnosis where the overall trend is more linear whereas the other diagnoses tend to have stronger effect during the diagnosis. It is surprising that the differences are so minimal, it might be that special healthcare catches a more homogenous group of depressions even though they receive different diagnoses once there. From another perspective it is also possible that untreated depression, mild or severe leads to similar outcomes and that even though we observe a diagnosis there remains many who don’t get better. The sum yearly visits with depression as the diagnosis per individual (Figure 3) might offer some insight as single visit has the highest density of the quantity of visits per year. Some of those might be simple that treatment has started late in the year and the next year treatment continues but this likely doesn’t explain all of the single visits. At the same time majority of those treated still receive only medication instead of medication and therapy and in general treatment is often considered inadequate (Hämäläinen et al. 2009).

The separation into different severities and durations by diagnoses gives little insight about the negative trend that depression has. As with the rest of the results including other sources of healthcare and ideally therapy as well, probably visible in the data obtained by Kela as they co-finance depression therapy, one might be able to see differences with severities and durations. Without being exactly sure that treatment has ended and of the quality of the treatment it is harder to draw conclusions about the effects between severities as one possibility is that to a degree the issue remains unsolved or has developed to another severity. It is also possible that depressed individuals after receiving a diagnosis recognize a kind of new reality in their lives and opt consistently for different jobs and activities regardless of the exact severity of their condition, especially considering that special healthcare cases are usually more severe. From this perspective it might be that the lowered earnings are not actually negative in nature but a sign of other preferences.

6.4 Earning groups

While the trends with the severities followed the general case closely, within the earning groups there are clear differences. These probably reflect differences between more fundamental characteristics of the groups. For example, it is clear that high earning individuals have better financial resources to respond to depression if they so choose to which could lead to earlier responses to depression and hence the effects of the depression to center closer to the diagnosis period.

In the low earnings segment the treatment and control group again start with a small difference in earnings but the decrease in earnings starts immediately with drastic drop during the year before the diagnosis. Compared to the general case though the earnings even increase slightly during the two years after the diagnosis before the effect levels off and remaining at a considerably lower level compared to control group or even the general case. The interaction effect at the end of the event from the regression is -4356 euros with r-squared of 0.315 and 5.4 million observations (Appendix 6). That effect of -4356 euros is compared to the control group, a similarly constructed low earning group who never in the data are shown to have received a depression diagnosis. If the comparison is done to the event study made on general population of the data the negative effect would be even more drastic, almost double. The statistical significance in the low earnings group regression is also very high and the confidence intervals in the predictive margins plot are very tight (Figure 11).

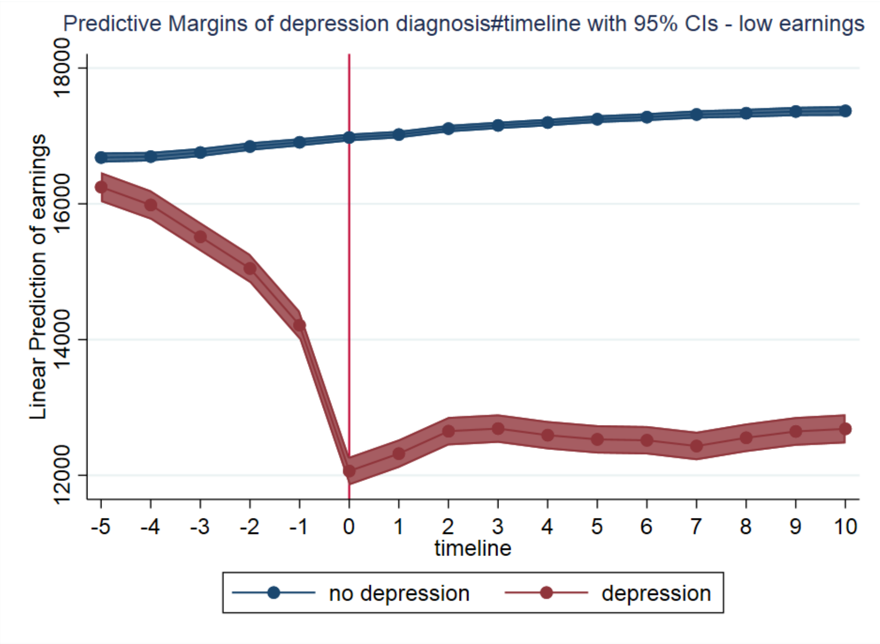

Figure 11. Predictive margins plot of low earning group with earnings as outcome and explanatory variable as the interaction of a binary variable signaling single mild / moderate depression diagnosis and the event window timeline of 16 years with year 0 being the year of the event, i.e. the diagnosis

The results of the middle earnings group differ from previous results in that the interaction effects prior to the diagnosis are not consistently negative and there is even a slight uptick the year before the diagnosis. However, after the event there is significant drop in earnings and a clear downwards trend till the end of the event window. The drop during the diagnosis year is approximately thousand euros with the end of the event showing an overall decrease of 3500 euros. The regression has an r-squared of 0.289 and over 6.5 million observations.

The larger confidence interval and the more level earnings prior to diagnosis hints at depression playing a lesser role in determining the earnings, perhaps the diagnosis is more accurately timed. The effect of the diagnosis however is clear and negative (Figure 12).

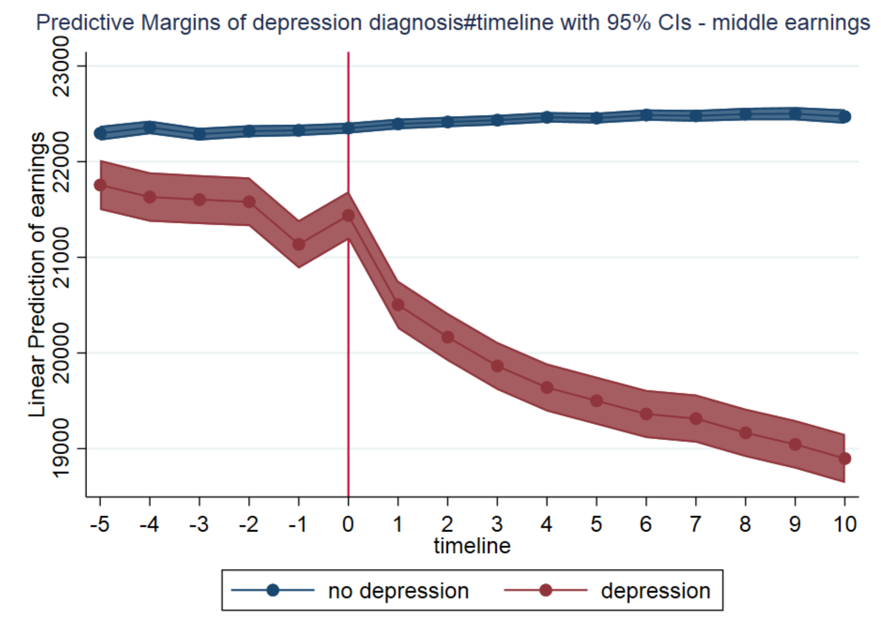

Figure 12. Predictive margins plot of middle earnings group with earnings as outcome and interaction of a binary variable of any depression diagnosis and event window timeline of 16 years with year 0 being the year of the event, i.e. diagnosis

The high and top earning groups have significantly different results and trends compared to the two previous groups. They share a similar trend with each other and in both the confidence interval for the treatment group is clearly larger than in previous cases. This is due to the much lower number of observations in the treatment group. In both high and top earning cases the treatment and control group start at more or less the same level and in the high earning case the treatment group contrary to all the previous cases starts to increase its earnings immediately which continues until the diagnosis. The interaction effect in the year of the event is over 6000 euro higher compared to the control group. After the diagnosis there is three years of clear drop with the negative trend continuing till the end of the event window (Figure 13). At the end of the event window the treatment group is approximately 6000 euro lower in yearly earnings compared to control group.

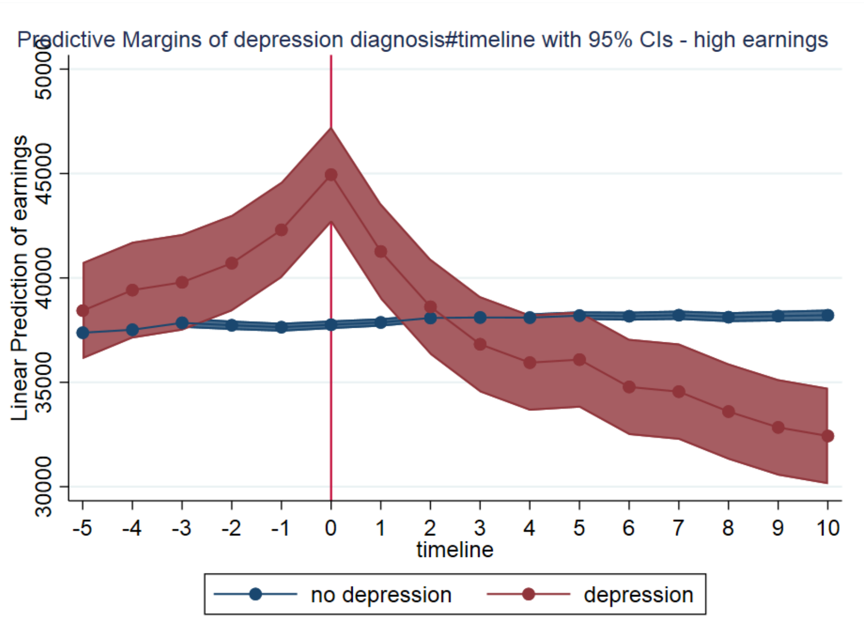

Figure 13. Predictive margins plot of high earnings group with earnings as outcome and interaction of a binary variable of any depression diagnosis and event window timeline of 16 years with year 0 being the year of the event, i.e. diagnosis

In the top earning group, the effect prior to diagnosis is more modest and follows the control group more closely but the peak increase in earnings is even higher during the diagnosis year at almost 30000 euros. Consequently, the drop is larger as well but contrary to the high earning case the negative trend levels off faster and earnings with confidence interval taken into consideration remains statistically not significantly different from the control group. Only the last year show slight statistical difference and lower earnings compared to control group. The last two years show around 16000€ difference from control group (Figure 14).

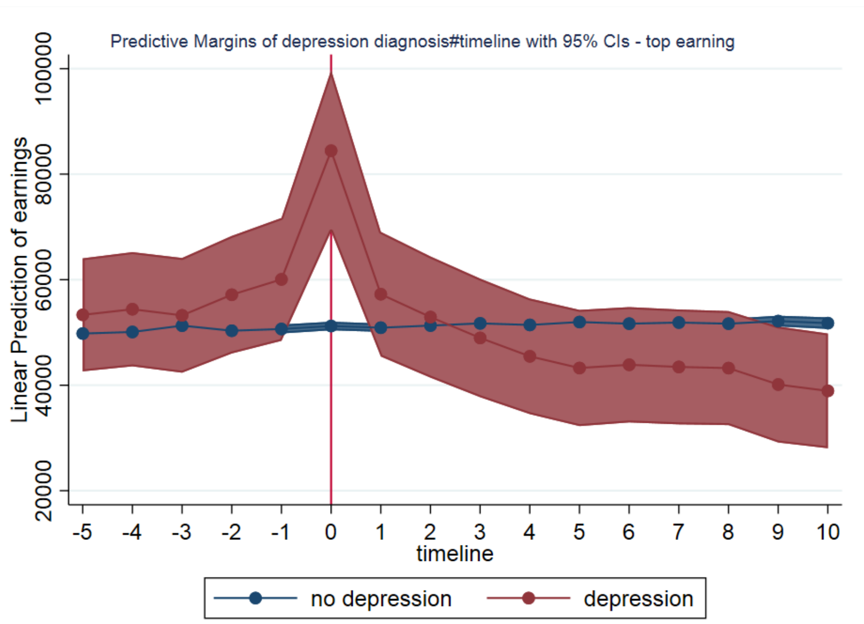

Figure 14. Predictive margins plot of top earnings group with earnings as outcome and interaction of a binary variable of any depression diagnosis and event window timeline of 16 years with year 0 being the year of the event, i.e. diagnosis

There are various reasons why the earning groups differ especially in the trends across the event window. The magnitude by which the earnings differ is perhaps less interesting than the differing trends between them as it is only natural that for higher earnings the effects are larger in absolute terms. For the high earners it is probable that overworking and work-related stress play a significant factor. Overtime statistics and performance related bonuses would be interesting to include in the observations separately. In this study bonuses are included in the earnings variable but are not distinguishable from the other earning varieties and no indication of hours worked is available in the data. As burnout currently is not a valid medical diagnosis and thus because the symptoms are often very similar to depression and suffering from burnout might well lead to depression, or vice versa, much of these cases at the high earning groups might be burnout related. It seems then that in higher earning groups the depression diagnosis might capture a different cause of depression compared to lower earning groups.

For the lower earning groups, the negative effects start before diagnosis and thus might hint at either hidden depression or other issues that also have an effect on labour market outcomes and possibly on depression itself. Arguably it is a combination of both of these factors. Multiple problems such as addictions and health issues are perhaps more common in lower socioeconomic positions. Those at lower socioeconomic position logically have less resources in their disposal for healthcare purposes which can prolong the period between the onset of depression and its diagnosis. As such, the causes and effects of the depressions between individuals are likely different and harder to pinpoint as they might vary significantly. It is probable that the health control included in the regressions is not adequate in determining the overall health of an individual as it only counts the number of visits not related to depression to special healthcare.

In general, it seems that the diagnosis and hence treatment is inadequate in there is no convergence to the previous levels of earnings. It seems that most depressed, especially considering that most of the ones receiving special healthcare services do reside in lower earning groups, suffer from a significant and permanent negative shock in the labour markets.

7. Conclusions

The short-term effects of depression on labour market outcomes are in line with much of the literature reviewed in this study. The main result from this study is the effect of depression on earnings. An average effect of the diagnosis of all major depressions in the year of the diagnosis on yearly earnings is approximately -3000 euros, a little over the mean monthly salary of Finland. The event studies constructed from the interaction of the first depression diagnosis and the timeline around it were used to study the long-term effects of depression. These events were studied for various severities and in different earning categories. The baseline with all diagnoses shows a decreasing trend in yearly earnings since the beginning of the timeline with effects during the diagnosis year similar to those found in the standard OLS regressions. The trend continues negative after the diagnosis and at the end of the event, 10 years after first diagnosis, the baseline depressed stand at approximately 4300 euros lower than those never having been diagnosed with depression. The direction and trend change very little between different severities or durations of depressions. Magnitudes behave logically with more severe depressions experiencing more negative effects. For example, recurring severe depression the effect at 10 years after is approximately -5000 euros in yearly earnings.

Most interesting results are those where the event population is divided into 4 different earning groups. The lowest group behaved similar to the whole population-based results pre diagnosis with the difference that the magnitudes are stronger. After diagnosis however the yearly earnings level off and remain there till the 10 years after. The middle group sees less consistent behavior before diagnosis but otherwise the effects are similar to those of baseline. The highest earning two groups behave completely differently to the previous findings. They demonstrate strong increases in yearly earnings arriving to the first diagnosis at which point the decrease is abrupt and strong. The stark difference between different earning levels is likely due to different causes of depression. At high earning groups the increased earnings and even clearer decrease are likely related to over working and burnout and the subsequent disability leave though this is not explored further in this study. All in all, even with the increased earnings till the diagnosis for the higher earning groups, the effect of depression in the long-term looks bleak.

The negative long-term results are quite disconcerting considering that the identification of depression in this study is based on treatment. This would suggest that even with treatment the depressed find it difficult to converge with their previous level of yearly earnings long after depression. Of course, it is impossible to estimate exactly what happens to the depressed that go untreated. Considering that recurring depressions, i.e. treatment has not succeeded in reaching symptomless state, do show stronger negative effects it is probable that the untreated fare even worse. It is also possible that the treatment received has been inadequate and that might explain some of the continued negative effects in long-term. Hämäläinen et al. (2009) found that 54% of those treated received minimal adequate treatment though they also found that special healthcare was perceived considerately more helpful than primary care. It might also be that the diagnosis is not precise enough in determining the level of disability experienced by those depressed. There is evidence that symptoms vary significantly in their debilitating effect (Banerjii et al. 2017, Velázquez R.G, 2019) and studying the remission of certain symptoms might help shed light as to what keeps the earnings from increasing. On the other hand, it is completely possible that the estimated decreased earnings are not a negative feature rather a sign of depressed opting for type of work which might be less stressful or otherwise more pleasant even if the monetary rewards are lower.

If the effect on yearly earnings during the year of the diagnosis are extrapolated to the whole population with major depressive disorder in Finland the aggregate decrease in earnings would be around 828 million euros to 1.16 billion euros. This is based on the estimates of major depressive disorder prevalence during the past 12 months in Finland hovering around 5-7% (Markkula et al. 2017, Hämäläinen et al. 2009). This might be an overestimate however as special healthcare depression cases are likely more severe. Additionally, it is possible that some of that effect is due to reverse causality or unobserved bias. On the other hand, considering that lifetime prevalence rates of major depressive disorder are even higher, and the long-term effects found in this study are persistent and even stronger than short-term effects, the aggregate yearly decrease in earnings caused by depression might be even higher.

What is clear is that depression is expensive both to individuals and society. Future research in this topic could include a better symptom based explanatory variables with otherwise similar data and methods. As for this thesis, it could be extended to include better controls for overall health, which ought to be possible with the data available. Additionally, combining primary healthcare data would give credibility as to what the aggregate effects are for the whole population, not just those under special healthcare. Including more labour market outcomes and using more robust models in estimating the effect of depression on them than standard OLS would shed light to the path through which depression is decreasing earnings.

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Appendix

Appendix 1. Descriptive statistics over different depression diagnoses

	Gender	Age	Highest ed. level	Earnings	Employment months	Non-dep. visits to SHC
No depression diagnosis						
mean	0.49	40.49	3.28	17081.53	10.25	0.84
p25	0.00	31.00	3.00	1637.89	11.00	0.00
p50	0.00	41.00	3.00	16446.38	12.00	0.00
p75	1.00	51.00	5.00	25391.08	12.00	0.00
N	63517033.00	63517033.00	63517033.00	62953119.00	48994190.00	63517033.00
max	1.00	60.00	8.00	47046788.00	12.00	1153.00
min	0.00	20.00	0.00	0.00	0.00	0.00
sd	0.50	11.68	2.19	23188.95	3.48	3.90
All depressions						
mean	0.64	40.46	2.89	7351.39	8.92	4.99
p25	0.00	30.00	0.00	0.00	6.00	0.00
p50	1.00	41.00	3.00	647.53	12.00	2.00
p75	1.00	51.00	3.00	13196.16	12.00	6.00
N	579049.00	579049.00	579049.00	574865.00	324920.00	579049.00
max	1.00	60.00	8.00	726201.06	12.00	431.00
min	0.00	20.00	0.00	0.00	0.00	0.00
sd	0.48	11.96	2.13	11035.67	4.18	10.82
Single mild/moderate						
mean	0.64	40.19	2.91	8084.73	8.99	4.86
p25	0.00	29.00	0.00	0.00	6.00	0.00
p50	1.00	41.00	3.00	1829.38	12.00	2.00
p75	1.00	51.00	4.00	15028.70	12.00	6.00
N	212111.00	212111.00	212111.00	210815.00	128489.00	212111.00
max	1.00	60.00	8.00	615178.25	12.00	431.00
min	0.00	20.00	0.00	0.00	0.00	0.00
sd	0.48	12.06	2.10	11243.31	4.14	10.02
singe severe						
mean	0.61	41.64	2.79	5957.16	8.55	5.01
p25	0.00	31.00	0.00	0.00	5.00	0.00
p50	1.00	44.00	3.00	0.00	12.00	2.00
p75	1.00	52.00	3.00	8958.62	12.00	6.00
N	103697.00	103697.00	103697.00	103090.00	51551.00	103697.00
max	1.00	60.00	8.00	615178.25	12.00	363.00
min	0.00	20.00	0.00	0.00	0.00	0.00
sd	0.49	12.10	2.12	10665.83	4.37	10.44
recurring mild moderate						
mean	0.70	40.90	3.13	7779.09	9.30	4.83
p25	0.00	31.00	3.00	0.00	7.00	0.00
p50	1.00	42.00	3.00	1134.26	12.00	2.00
p75	1.00	51.00	5.00	14368.85	12.00	6.00
N	124787.00	124787.00	124787.00	124209.00	72452.00	124787.00
max	1.00	60.00	8.00	245466.97	12.00	291.00
min	0.00	20.00	0.00	0.00	0.00	0.00
sd	0.46	11.36	2.12	10957.21	3.98	9.92
recurring severe						
mean	0.67	42.43	3.02	5696.61	8.89	5.13
p25	0.00	33.00	3.00	0.00	5.00	0.00
p50	1.00	44.00	3.00	0.00	12.00	2.00
p75	1.00	52.00	5.00	8244.41	12.00	6.00
N	67386.00	67386.00	67386.00	67116.00	32188.00	67386.00
max	1.00	60.00	8.00	726201.06	12.00	365.00
min	0.00	20.00	0.00	0.00	0.00	0.00
sd	0.47	11.40	2.13	10375.86	4.19	11.14
Dysthymia						
mean	0.64	42.04	2.89	5976.85	8.75	4.41
p25	0.00	32.00	0.00	0.00	5.00	0.00
p50	1.00	44.00	3.00	0.00	12.00	1.00
p75	1.00	53.00	5.00	9453.33	12.00	5.00
N	37437.00	37437.00	37437.00	37094.00	18059.00	37437.00
max	1.00	60.00	8.00	369377.53	12.00	363.00
min	0.00	20.00	0.00	0.00	0.00	0.00
sd	0.48	11.90	2.16	10067.44	4.36	10.09

Notes 4. Descriptive table of mean, 25th percentile, median, 75th percentile, number of observations, maximum and minimum observations and standard deviation for gender, age, highest level of education, earnings, employment months and number of non-depression visits to special healthcare

Appendix 2: Linear regressions of depression on earnings over 4 different earning groups

Low earning group	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: Earnings						
depression	-6957.3***	-6694.6***	-8359.7***	-2878.5***	-2922.6***	-2694.4***	-2734.9***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
gender		-2359.5***	-2714.8***	-3026.1***	-3157.6***	-3134.0***	-4433.4***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Nationality	No	Yes	Yes	Yes	Yes	Yes	Yes
Birth Origin	No	Yes	Yes	Yes	Yes	Yes	Yes
Native Language	No	Yes	Yes	Yes	Yes	Yes	Yes
Age	No	No	Yes	Yes	Yes	Yes	Yes
Year	No	No	Yes	Yes	Yes	Yes	Yes
County	No	No	Yes	Yes	Yes	Yes	Yes
Highest education l	No	No	No	Yes	Yes	Yes	Yes
Field of education	No	No	No	Yes	Yes	Yes	Yes
Principal occup.	No	No	No	Yes	Yes	Yes	Yes
Marital status	No	No	No	No	Yes	Yes	Yes
#Children under 3	No	No	No	No	Yes	Yes	Yes
#Children under 7	No	No	No	No	Yes	Yes	Yes
#Children under 18	No	No	No	No	Yes	Yes	Yes
#visits to SHC	No	No	No	No	No	Yes	Yes
SocioEcon. Position	No	No	No	No	No	No	Yes
Year of graduation	No	No	No	No	No	No	Yes
R-sq	0.002	0.010	0.111	0.294	0.296	0.296	0.394
N	50267325	50267325	50267325	50267325	50267325	50267325	26595467

Middle earning group	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: Earnings						
depression	-9354.4***	-8668.7***	-10633.4***	-4085.8***	-4037.0***	-3678.4***	-3609.1***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
gender		-4981.8***	-5205.5***	-5256.1***	-5327.8***	-5289.6***	-5682.5***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Nationality	No	Yes	Yes	Yes	Yes	Yes	Yes
Birth Origin	No	Yes	Yes	Yes	Yes	Yes	Yes
Native Language	No	Yes	Yes	Yes	Yes	Yes	Yes
Age	No	No	Yes	Yes	Yes	Yes	Yes
Year	No	No	Yes	Yes	Yes	Yes	Yes
County	No	No	Yes	Yes	Yes	Yes	Yes
Highest education l	No	No	No	Yes	Yes	Yes	Yes
Field of education	No	No	No	Yes	Yes	Yes	Yes
Principal occup.	No	No	No	Yes	Yes	Yes	Yes
Marital status	No	No	No	No	Yes	Yes	Yes
#Children under 3	No	No	No	No	Yes	Yes	Yes
#Children under 7	No	No	No	No	Yes	Yes	Yes
#Children under 18	No	No	No	No	Yes	Yes	Yes
#visits to SHC	No	No	No	No	No	Yes	Yes
SocioEcon. Position	No	No	No	No	No	No	Yes
Year of graduation	No	No	No	No	No	No	Yes
R-sq	0.002	0.026	0.136	0.330	0.332	0.333	0.429
N	53248540	53248540	53248540	53248540	53248540	53248540	29600311

High earning group	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: Earnings						
depression	-12821.1***	-12242.6***	-17459.8***	-8986.6***	-8792.9***	-8113.2***	-7836.1***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
gender		-4726.6***	-5884.0***	-7651.7***	-7608.7***	-7546.5***	-7209.2***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Nationality	No	Yes	Yes	Yes	Yes	Yes	Yes
Birth Origin	No	Yes	Yes	Yes	Yes	Yes	Yes
Native Language	No	Yes	Yes	Yes	Yes	Yes	Yes
Age	No	No	Yes	Yes	Yes	Yes	Yes
Year	No	No	Yes	Yes	Yes	Yes	Yes
County	No	No	Yes	Yes	Yes	Yes	Yes
Highest education l	No	No	No	Yes	Yes	Yes	Yes
Field of education	No	No	No	Yes	Yes	Yes	Yes
Principal occup.	No	No	No	Yes	Yes	Yes	Yes
Marital status	No	No	No	No	Yes	Yes	Yes
#Children under 3	No	No	No	No	Yes	Yes	Yes
#Children under 7	No	No	No	No	Yes	Yes	Yes
#Children under 18	No	No	No	No	Yes	Yes	Yes
#visits to SHC	No	No	No	No	No	Yes	Yes
SocioEcon. Position	No	No	No	No	No	No	Yes
Year of graduation	No	No	No	No	No	No	Yes
R-sq	0.000	0.006	0.131	0.200	0.201	0.201	0.241
N	11076179	11076179	11076179	11076179	11076179	11076179	6771205

Top earning group	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: Earnings						
depression	-29430.9***	-27405.6***	-22599.7***	-3457.5***	-3061.2***	-3000.7***	-4536.1***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
gender		-10620.2***	-11186.2***	-9099.9***	-9268.3***	-9262.6***	-9235.0***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Nationality	No	Yes	Yes	Yes	Yes	Yes	Yes
Birth Origin	No	Yes	Yes	Yes	Yes	Yes	Yes
Native Language	No	Yes	Yes	Yes	Yes	Yes	Yes
Age	No	No	Yes	Yes	Yes	Yes	Yes
Year	No	No	Yes	Yes	Yes	Yes	Yes
County	No	No	Yes	Yes	Yes	Yes	Yes
topest ed. level	No	No	No	Yes	Yes	Yes	Yes
Field of education	No	No	No	Yes	Yes	Yes	Yes
Principal occup.	No	No	No	Yes	Yes	Yes	Yes
Marital status	No	No	No	No	Yes	Yes	Yes
#Children under 3	No	No	No	No	Yes	Yes	Yes
#Children under 7	No	No	No	No	Yes	Yes	Yes
#Children under 18	No	No	No	No	Yes	Yes	Yes
#visits to SHC	No	No	No	No	No	Yes	Yes
SocioEcon. Position	No	No	No	No	No	No	Yes
Year of graduation	No	No	No	No	No	No	Yes
R-sq	0.001	0.019	0.089	0.153	0.156	0.156	0.154
N	3797363	3797363	3797363	3797363	3797363	3797363	2007799

Notes: Linear regression of earnings with depression diagnosis as explanatory variable. Lists regressions on 4 different earning groups, categorization of those groups is explained in section 3. Methodology. Same controls are used as with all the other regressions in this study. These regressions are of the whole data of years 1995-2016. Effect is in yearly earnings in euros that are inflation adjusted with 1995 as base year.

Appendix 3. Linear regression of depression on employer company ownership (public/private)

	Dependent variable: Public sector (binary)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Depression diagnosis	0.0727***	0.0290***	0.0469***	0.0439***	0.0437***	0.0363***	0.0171***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gender		0.228***	0.225***	0.109***	0.109***	0.108***	0.0608***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Nationality	No	Yes	Yes	Yes	Yes	Yes	Yes
Birth Origin	No	Yes	Yes	Yes	Yes	Yes	Yes
Native Language	No	Yes	Yes	Yes	Yes	Yes	Yes
Age	No	No	Yes	Yes	Yes	Yes	Yes
Year	No	No	Yes	Yes	Yes	Yes	Yes
County	No	No	Yes	Yes	Yes	Yes	Yes
Highest ed. level	No	No	No	Yes	Yes	Yes	Yes
Field of ed.	No	No	No	Yes	Yes	Yes	Yes
Principal occup.	No	No	No	Yes	Yes	Yes	Yes
Marital status	No	No	No	No	Yes	Yes	Yes
#Kids under 3	No	No	No	No	Yes	Yes	Yes
#Kids under 7	No	No	No	No	Yes	Yes	Yes
#Kids under 18	No	No	No	No	Yes	Yes	Yes
#visits to SHC	No	No	No	No	No	Yes	Yes
SocioEcon. Position	No	No	No	No	No	No	Yes
Year of graduation	No	No	No	No	No	No	Yes
R-sq	0.000	0.061	0.089	0.203	0.204	0.204	0.333
N	45954132	45954132	45954132	45954132	45954132	45954132	25824766

Notes: Linear regression of the ownership of the company where individual is employed. It is a binary outcome variable determining whether the company is publicly (1) or privately (0) owned. Linear regression is not well suited to estimate the effect on such outcome variable.

Appendix 4: Linear regression of the interaction of specific diagnosis and 16 year event window on earnings

Single mild / moderate diagnosis:

Dependent variable: Earnings

	No depression		Depression	
	b	ci95	b	ci95
depression diagnosis ever	0	[0 , 0]	-546**	[-927 , -165]
*Depression * timeline interaction*				
year: -5	0	[0 , 0]	0	[0 , 0]
year: -4	56	[-26 , 138]	-281	[-818 , 256]
year: -3	121**	[35 , 206]	-552*	[-1089 , -16]
year: -2	103*	[14 , 191]	-521	[-1056 , 15]
year: -1	128**	[36 , 220]	-830**	[-1364 , -295]
year: 0	179***	[84 , 275]	-1373***	[-1907 , -838]
year: 1	219***	[120 , 319]	-1839***	[-2373 , -1305]
year: 2	269***	[165 , 373]	-1983***	[-2516 , -1450]
year: 3	307***	[199 , 414]	-2165***	[-2697 , -1633]
year: 4	323***	[212 , 434]	-2334***	[-2866 , -1803]
year: 5	342***	[227 , 456]	-2442***	[-2973 , -1911]
year: 6	322***	[204 , 440]	-2430***	[-2961 , -1900]
year: 7	351***	[230 , 472]	-2595***	[-3125 , -2064]
year: 8	316***	[191 , 440]	-2579***	[-3109 , -2049]
year: 9	313***	[185 , 441]	-2573***	[-3103 , -2043]
year: 10	302***	[169 , 434]	-2779***	[-3308 , -2249]
Controls	Yes			
R-squared	0.289			
Observations	6961151			

Single severe diagnosis:

Dependent variable: Earnings

	No depression		Depression	
	b	ci95	b	ci95
depression diagnosis ever	0	[0 , 0]	-641*	[-1265 , -16]
*Depression * timeline interaction*				
year: -5	0	[0 , 0]	0	[0 , 0]
year: -4	40	[-41 , 120]	4	[-877 , 885]
year: -3	63	[-20 , 147]	-148	[-1027 , 730]
year: -2	24	[-63 , 111]	-429	[-1307 , 448]
year: -1	14	[-77 , 104]	-647	[-1524 , 230]
year: 0	9	[-85 , 103]	-1219**	[-2095 , -343]
year: 1	37	[-61 , 135]	-1781***	[-2657 , -905]
year: 2	56	[-46 , 158]	-2042***	[-2917 , -1168]
year: 3	96	[-9 , 202]	-2268***	[-3142 , -1395]
year: 4	91	[-18 , 200]	-2480***	[-3353 , -1607]
year: 5	100	[-12 , 213]	-2921***	[-3793 , -2049]
year: 6	123*	[7 , 238]	-3067***	[-3938 , -2196]
year: 7	73	[-46 , 192]	-3076***	[-3947 , -2206]
year: 8	51	[-71 , 174]	-3199***	[-4069 , -2329]
year: 9	21	[-105 , 147]	-3298***	[-4167 , -2428]
year: 10	-26	[-157 , 104]	-3314***	[-4184 , -2444]
Controls	Yes			
R-squared	0.299			
Observations	6888801			

Recurring severe diagnosis:

Dependent variable: Earnings

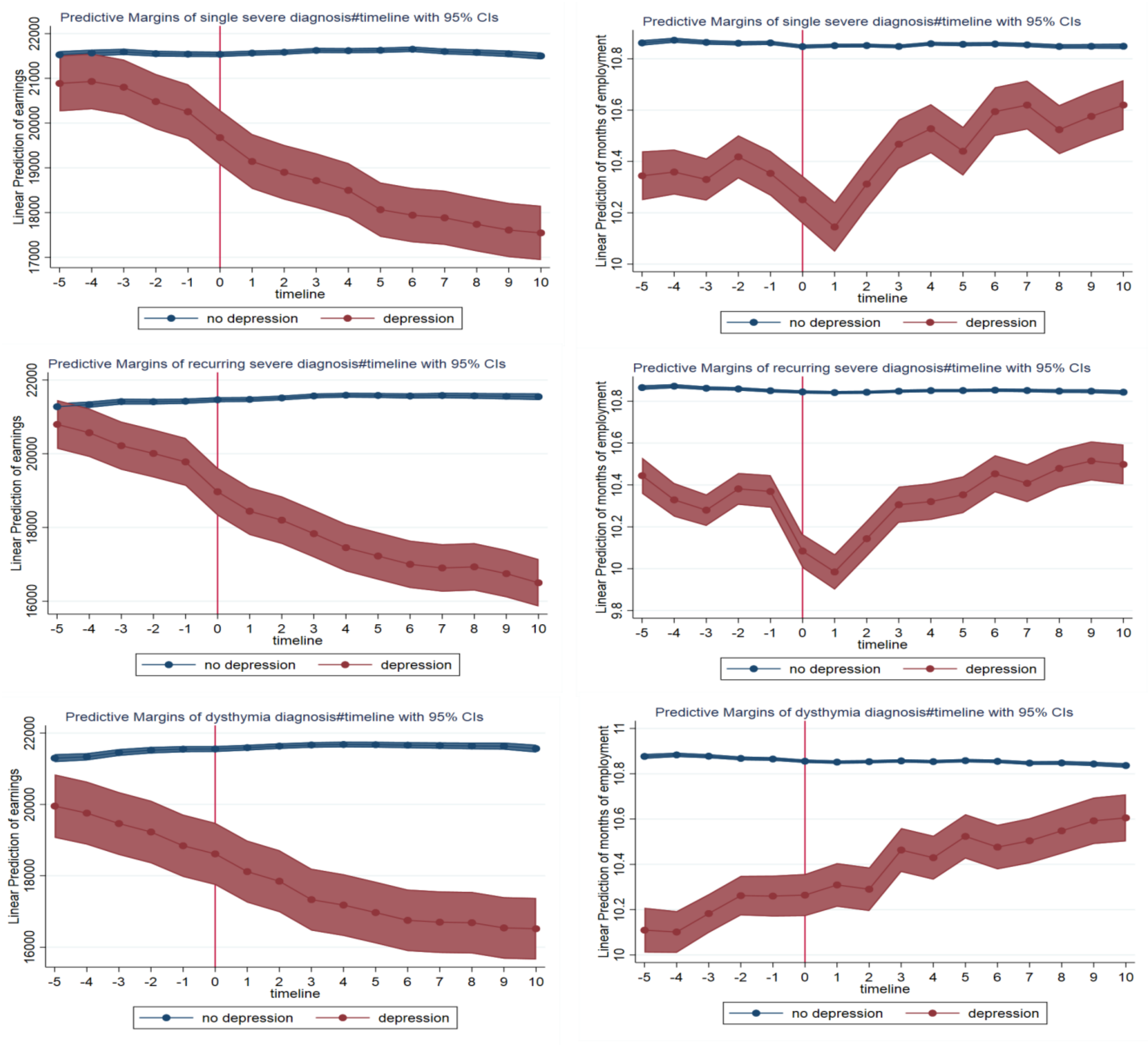
	No depression		Depression	
	b	ci95	b	ci95
depression diagnosis ever	0	[0 , 0]	-480	[-1141 , 181]
*Depression * timeline interaction*				
year: -5	0	[0 , 0]	0	[0 , 0]
year: -4	56	[-38 , 149]	-282	[-1214 , 651]
year: -3	138**	[41 , 235]	-716	[-1647 , 214]
year: -2	135**	[34 , 235]	-922	[-1851 , 6]
year: -1	148**	[44 , 252]	-1164*	[-2092 , -237]
year: 0	188***	[80 , 297]	-2016***	[-2943 , -1089]
year: 1	197***	[84 , 310]	-2552***	[-3478 , -1626]
year: 2	237***	[119 , 355]	-2835***	[-3760 , -1909]
year: 3	292***	[170 , 414]	-3256***	[-4181 , -2332]
year: 4	312***	[186 , 438]	-3656***	[-4580 , -2732]
year: 5	305***	[175 , 435]	-3876***	[-4799 , -2953]
year: 6	290***	[156 , 424]	-4086***	[-5009 , -3163]
year: 7	304***	[166 , 442]	-4199***	[-5122 , -3275]
year: 8	295***	[153 , 436]	-4159***	[-5082 , -3237]
year: 9	283***	[137 , 428]	-4331***	[-5253 , -3410]
year: 10	271***	[120 , 422]	-4567***	[-5488 , -3646]
Controls	Yes			
R-squared	0.240			
Observations	6894025			

Dysthymia diagnosis:

Dependent variable: Earnings

	No depression		Depression	
	b	ci95	b	ci95
depression diagnosis ever	0	[0 , 0]	-1344**	[-2233 , -456]
*Depression * timeline interaction*				
year: -5	0	[0 , 0]	0	[0 , 0]
year: -4	38	[-73 , 150]	-234	[-1487 , 1019]
year: -3	158**	[42 , 274]	-646	[-1898 , 606]
year: -2	222***	[102 , 343]	-948	[-2198 , 302]
year: -1	252***	[127 , 377]	-1363*	[-2610 , -116]
year: 0	256***	[126 , 386]	-1595*	[-2841 , -350]
year: 1	293***	[157 , 428]	-2129***	[-3374 , -884]
year: 2	337***	[196 , 478]	-2442***	[-3686 , -1198]
year: 3	369***	[223 , 515]	-2991***	[-4234 , -1748]
year: 4	383***	[232 , 534]	-3157***	[-4398 , -1915]
year: 5	377***	[222 , 533]	-3361***	[-4602 , -2121]
year: 6	363***	[203 , 524]	-3564***	[-4804 , -2325]
year: 7	352***	[187 , 517]	-3605***	[-4844 , -2366]
year: 8	342***	[173 , 511]	-3610***	[-4849 , -2371]
year: 9	337***	[162 , 511]	-3751***	[-4989 , -2513]
year: 10	268**	[88 , 449]	-3705***	[-4942 , -2468]
Controls	Yes			
R-squared	0.184			
Observations	6884933			

*Notes: Linear regression on earnings with an interaction between depression diagnosis (ever having had one) and 16-year timeline as an explanatory variable where year 0 is the year of first diagnosis of depression. For the control group, i.e. the individuals who have never received a depression diagnosis, the year 0 is a fake and randomly assigned "event". Depression diagnosis ever shows the effect of belonging to the treatment group and the depression * timeline interaction shows the yearly effects. All the same controls are included as in the standard linear regression of before. All together 4 different regressions are shown each with a different severity of depression diagnosis as an explanatory variable. Differences also exist in the duration of the diagnoses as recurring and dysthymia are by nature longer duration than single episodes. Creating the treatment groups is done so that milder severities could not have stronger diagnoses present in their timeline but stronger severity diagnoses could include milder ones, only that their first diagnosis, meaning the event, is in any case the diagnosis under which they are grouped.*



Appendix 1. Visual representations of the appendix 4. Also shows employment months predictive margins plots.

Appendix 6: Linear regression of the interaction of depression diagnosis and 16 year event window on earnings over 4 different earning groups

Low earning group

Dependent variable: Earnings

		No depression		Depression	
		b	ci95	b	ci95
	depression diagnosis ever	0	[0 , 0]	-435***	[-653 _ -216]
Depression * timeline interaction	year: -5	0	[0 , 0]	0	[0 , 0]
	year: -4	14	[-62 , 90]	-278	[-585 , 30]
	year: -3	74	[-5 , 153]	-806***	[-1113 , -500]
	year: -2	163***	[81 , 244]	-1362***	[-1668 , -1056]
	year: -1	225***	[140 , 310]	-2260***	[-2566 , -1954]
	year: 0	296***	[208 , 384]	-4480***	[-4786 , -4174]
	year: 1	339***	[247 , 431]	-4267***	[-4572 , -3961]
	year: 2	426***	[331 , 522]	-4023***	[-4328 , -3718]
	year: 3	474***	[375 , 572]	-4032***	[-4337 , -3727]
	year: 4	516***	[414 , 618]	-4172***	[-4476 , -3867]
	year: 5	566***	[460 , 671]	-4283***	[-4587 , -3979]
	year: 6	596***	[488 , 704]	-4326***	[-4630 , -4022]
	year: 7	634***	[523 , 745]	-4450***	[-4753 , -4146]
	year: 8	653***	[539 , 767]	-4347***	[-4651 , -4043]
	year: 9	678***	[561 , 796]	-4278***	[-4582 , -3975]
	year: 10	688***	[566 , 809]	-4250***	[-4553 , -3946]
	Controls	Yes			
	R-squared	0.315			
	Observations	5436756			

Middle earning group

Dependent variable: Earnings

		No depression		Depression	
		b	ci95	b	ci95
	depression diagnosis ever	0	[0 , 0]	-541***	[-801 , -281]
Depression * timeline interaction	year: -5	0	[0 , 0]	0	[0 , 0]
	year: -4	61	[-15 , 138]	-187	[-554 , 180]
	year: -3	-10	[-89 , 70]	-143	[-509 , 223]
	year: -2	22	[-61 , 104]	-197	[-563 , 168]
	year: -1	30	[-55 , 116]	-651***	[-1016 , -286]
	year: 0	53	[-36 , 142]	-371*	[-736 , -6]
	year: 1	97*	[4 , 189]	-1349***	[-1714 , -985]
	year: 2	118*	[21 , 214]	-1708***	[-2072 , -1344]
	year: 3	137**	[37 , 237]	-2029***	[-2393 , -1665]
	year: 4	166**	[64 , 269]	-2284***	[-2648 , -1920]
	year: 5	158**	[52 , 264]	-2414***	[-2778 , -2051]
	year: 6	190***	[81 , 299]	-2584***	[-2948 , -2221]
	year: 7	182**	[70 , 294]	-2624***	[-2987 , -2261]
	year: 8	200***	[85 , 316]	-2792***	[-3155 , -2429]
	year: 9	204***	[86 , 323]	-2916***	[-3279 , -2553]
	year: 10	174**	[51 , 297]	-3034***	[-3397 , -2671]
	Controls	Yes			
	R-squared	0.289			
	Observations	6567478			

High earning group

Dependent variable: Earnings

		No depression		Depression	
		b	ci95	b	ci95
	depression diagnosis ever	0	[0 , 0]	1058	[-1262 , 3377]
Depression * timeline interaction	year: -5	0	[0 , 0]	0	[0 , 0]
	year: -4	141	[-132 , 415]	841	[-2435 , 4118]
	year: -3	475**	[191 , 760]	882	[-2393 , 4157]
	year: -2	356*	[61 , 651]	1918	[-1355 , 5191]
	year: -1	264	[-42 , 571]	3605*	[331 , 6878]
	year: 0	382*	[63 , 701]	6131***	[2858 , 9405]
	year: 1	491**	[159 , 824]	2343	[-931 , 5617]
	year: 2	706***	[359 , 1053]	-524	[-3795 , 2747]
	year: 3	730***	[371 , 1089]	-2341	[-5612 , 930]
	year: 4	725***	[354 , 1095]	-3216	[-6487 , 54]
	year: 5	820***	[438 , 1202]	-3166	[-6436 , 105]
	year: 6	791***	[397 , 1185]	-4446**	[-7716 , -1175]
	year: 7	839***	[435 , 1244]	-4719**	[-7990 , -1447]
	year: 8	744***	[328 , 1160]	-5578***	[-8848 , -2307]
	year: 9	799***	[371 , 1227]	-6391***	[-9662 , -3120]
	year: 10	839***	[395 , 1282]	-6842***	[-10111 , -3573]
	Controls	Yes			
	R-squared	0.156			
	Observations	1781119			

Top earning group

Dependent variable: Earnings

		No depression		Depression	
		b	ci95	b	ci95
	depression diagnosis ever	0	[0 , 0]	3539	[-7169 , 14247]
Depression * timeline interaction	year: -5	0	[0 , 0]	0	[0 , 0]
	year: -4	290	[-781 , 1361]	774	[-14449 , 15997]
	year: -3	1497**	[382 , 2612]	-1594	[-16850 , 13661]
	year: -2	528	[-633 , 1688]	3287	[-12165 , 18740]
	year: -1	858	[-349 , 2065]	5864	[-9960 , 21689]
	year: 0	1424*	[165 , 2683]	29690**	[11018 , 48362]
	year: 1	1105	[-210 , 2419]	2809	[-13143 , 18761]
	year: 2	1512*	[140 , 2883]	-1932	[-17642 , 13779]
	year: 3	1924**	[503 , 3345]	-6298	[-21827 , 9231]
	year: 4	1626*	[157 , 3096]	-9491	[-24820 , 5837]
	year: 5	2183**	[665 , 3700]	-12258	[-27622 , 3106]
	year: 6	1867*	[302 , 3432]	-11330	[-26627 , 3966]
	year: 7	2081*	[470 , 3692]	-11956	[-27224 , 3312]
	year: 8	1868*	[210 , 3526]	-11962	[-27171 , 3246]
	year: 9	2358**	[650 , 4065]	-15567*	[-30905 , -230]
	year: 10	1966*	[196 , 3735]	-16379*	[-31624 , -1135]
	Controls	Yes			
	R-squared	0.155			
	Observations	445635			

*Notes: Linear regression on earnings with an interaction between depression diagnosis (ever having had one) and 16-year timeline as an explanatory variable where year 0 is the year of first diagnosis of depression. For the control group, i.e. the individuals who have never received a depression diagnosis, the year 0 is a fake and randomly assigned "event". Depression diagnosis ever shows the effect of belonging to the treatment group and the depression * timeline interaction shows the yearly effects. All the same controls are included as in the standard linear regression of before. All together 4 different regressions are shown each constructed of different earning groups. The groups are formed so that individual could be present in more than one group so that earnings could change along the timeline freely.*